THE INCREMENTAL INFORMATION CONTENT OF ANALYSTS' RESEARCH REPORTS AND FIRMS' ANNUAL REPORTS: EVIDENCE FROM TEXTUAL ANALYSIS

JUNE WOO PARK

A DISSERTATION SUBMITTED TO

THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

GRADUATE PROGRAM IN ACCOUNTING

YORK UNIVERSITY

TORONTO, ONTARIO

JUNE 2019

Abstract

This dissertation consists of three essays, investigating the properties of analysts' research reports and firms' annual reports, and their impact on capital markets using textual analysis methods.

The first essay studies the validity of analyst report length, measured by page count, as a proxy for analysts' research effort. Specifically, I find that longer reports are more positively associated with recommendation upgrades than downgrades, and with forecast accuracy. I further document an asymmetric market reaction to longer upgrades as compared to the same length downgrades. Cross-sectional tests find that this asymmetric report length effect is greater for longer upgrade reports with more cash flow discussion, by less experienced, busier, or male analysts, for high opaque firms, or during a financial crisis. The findings support my hypothesis that by providing more and accurate information, analysts exert credibility-enhancing efforts on their upgrades, as these are perceived by investors to be more optimistic and less credible than downgrades. The study is the first comprehensive investigation of analysts' research effort for U.S. firms using the number of pages in their reports and suggests differing interpretations of analyst vs. annual report length as a proxy. In other words, management tends to write a longer annual report to hide bad news, whereas analysts tend to write a longer analyst report to provide, and not hide, more information to increase report credibility.

In a second textual analysis essay, I examine the determinants of environmental disclosures (ED) in U.S. 10-Ks (i.e. annual reports) and its impact on future stock price crash risk. I provide crucial evidence that ED is related to bad news (i.e. news that tends to be obfuscated by managers) by showing the autocorrelation of its change over time and its negative association with short-term market reaction. In the long run, however, an increase in ED shows a

lower likelihood of significant stock price drops. Change and instrument variable analyses mitigate endogeneity and identify a potential causality of ED on the future crash risk. The results are consistent with the notion that firms benefit from non-financial information disclosure.

A third textual analysis essay compares the value of private versus public information sources in U.S. analysts' earnings forecasts. Using a pattern search algorithm (i.e., regular expression) on the headlines of earnings forecasts, I find that additional private sources of information are associated with (or may cause) less forecast error, triggering a greater market reaction. Moreover, I document that the combination of management and non-management private information sources minimizes forecast error and maximizes market reaction. Thus, such a combination tends to produce the most accurate forecasts and, as a result, the strongest market reaction. Finally, I show that more accurate and informative forecasts are made by analysts who make greater efforts to access private information sources, even when they do not have other information advantages (e.g. brokerage firm reputation). Thus, I provide new insight into the determinants of forecast properties.

Overall, the above-noted studies show that the length and the information sources of analysts' research reports significantly influence investors' decision making. The essays also suggest that environmental disclosure in firms' annual reports contributes to a decrease in future stock price crash risk.

Acknowledgments

First of all, I would like to thank my dissertation committee: Dr. Albert Tsang (chair), Dr. Kiridaran (Giri) Kanagaretnam, Dr. Kee-Hong Bae, Dr. Gary Spraakman, and Dr. Tracy (Kun) Wang for their advice and constructive feedback on my dissertation.

Especially, I would like to acknowledge my deepest gratitude to Dr. Albert Tsang, my supervisor and thesis advisor, for his invaluable detailed guidance, thoughtful correction, his confidence in my ability to carry the work out, and his great encouragement at each stage of my doctoral studies. This thesis would not have been possible without his wisdom, feedback, and support. Thank you for also being my friend and family.

I am incredibly fortunate to have Dr. Hongping Tan, my former advisor. His constant support and guidance have made my PhD study a fruitful journey. I will be forever indebted to you.

I am also highly indebted to Dr. Kee-Hong Bae, my mentor. I appreciate his insightful comments and continuing encouragement throughout the process. He is very kind and supportive. This thesis has been considerably improved as a result of his insightful suggestions.

I greatly thank Dr. Kiridaran (Giri) Kanagaretnam for caring me like a big brother. Your guidance and philosophy have shaped my thinking not only in research but also in life. There are no words that can truly express my gratitude to you for everything.

This journey would not have been possible without the great support that I have received from my family over the years.

I have to say thank you to my loving parents, Hyun Soo Park and Song Gang Kim. I would like to express my sincere gratitude for raising me to be who I am today with your

unconditional love. I thank you for supporting me in everything I wanted to do in life. I could not have hoped for better parents. I earnestly pray for my father's fast and easy recovery.

Table of Contents

The Determinants and Consequences of Analyst Report Length

Abstract

Based on textual analysis of 351,629 analyst reports for US firms over 2000-2014, the study finds that analysts tend to generate longer reports for recommendation upgrades rather than downgrades. Compared to shorter reports, longer reports are more accurate in earnings forecast, but solicit a stronger market reaction to upgrades perceived to less credible than downgrades. This suggests that analysts dedicate greater research efforts on the credibility/quality of upgrades by providing more information. The market reaction to longer upgrades is more pronounced when analysts discuss more about a firm's cash flow; are less experienced, busier, and a male; cover firms with a higher level of information asymmetry; and are issued during a financial crisis. Overall, the study shows a contrast between *analyst* and *annual* report length.

Keywords: Report Length, Research Effort, Accuracy, Credibility, Informativeness, Valuation Detail

1. Introduction

Managers use longer *annual* reports (i.e., Form 10-Ks) generally to obfuscate/hide bad news (e.g., Loughran and McDonald, 2014). In contrast, analysts have a different motivation to issue longer *research* reports because as an important intermediary in the capital market, analysts undertake great efforts to collect both public and private information and provide research reports to assess the valuation of the covered firms. These analyst reports contain both narratives and non-narratives (e.g., tables, charts, graphs, or pictures) to reflect their investment opinions and the underlying justifications. Comparing with *annual* report length, this study explores the validity of *analyst* report length, measured by page count, as a proxy for analysts' research effort.

Counting the number of pages in analyst reports, Feldman, Gilson, and Villalonga (2010) find that analysts' earnings forecasts increases with report length. Loh and Stulz (2018) document that analysts work harder in bad times because investors rely more on analysts when investor uncertainty is heightened. In one of their robustness tests, Loh and Stulz (2018) find that analysts working for Morgan Stanley write longer reports in bad times, suggesting that analysts exert more effort in incorporating more information in the report.

The findings of these two studies are in sharp contrast to those of prior studies showing that management uses longer 10-K filings to obfuscate bad news. Analysts' motivation to provide additional information in response to investors' demand (Loh and Stulz 2018) or their own needs (Feldman, Gilson, and Villalonga 2010) brings about a longer research report, whereas management's intention to hide bad news results in a longer annual report (e.g., Loughran and McDonald, 2014).

Counting the number of words and sentences in stand-alone CSR reports, Clarkson, Ponn, Richardson, Rudzicz, Tsang, and Wang (2018) find a positive association between CSR performance and CSR report length, as predicted by signaling theory. This suggests that analysts *signal* their overall research effort through report length.

This study examines the determinants and implications of report length based on analyst reports from seven large investment banks over 2000-2014 from Investext. The paper first identifies the determinants of report length. Prior research (e.g., Boni and Womack, 2006; Jegadeesh and Kim, 2010) finds that recommendation revisions (i.e., upgrade and downgrade) convey new and useful information (e.g., Womack, 1996; Jagadeesh, Kim, Krische and Lee, 2004), and are more informative than mere levels (i.e., buy and sell) (e.g., Boni and Womack, 2006; Jegadeesh and Kim, 2010), suggesting that a change in analysts' prior belief better reflects their research effort. Moreover, due to analysts' conflicts of interest and/or desire for access to management (e.g., Michaely and Womack, 1999; Ke and Yu, 2006; Ljungqvist, Marston, Starks, Wei, and Yan, 2007), analysts tend to initially write favorable level recommendations (i.e., buy/hold) perceived to be less credible by investors. Because favorable levels outnumber unfavorable ones, it is less likely to for analysts to revise the former upwardly than downwardly, resulting in fewer upgrades than downgrades. Nevertheless, if analysts make upgrades, then the credibility of upgrades will be much less credible than favorable levels. Thus, this study focuses on analyst reports with the revisions, i.e., upgrade or downgrade reports, which provide a better research environment for a credibility test.

Specifically, on the information supply side, the paper documents that report length is more positively correlated with upgrade than downgrade, indicating research effort on credibility enhancement by providing more information in upgrade inherently perceived to be less credible (Conrad, Cornell, Landsman, and Rountree, 2006). Report length also has a more positive association with post-earnings announcements (analyst team) because of more resources available. However, report length is negatively correlated with a firm's past return volatility since the costs of covering the firm might outnumber its benefits. On the information demand side, report length is positively related to a financial crisis period and recession to respond to investors' greater demand for information. This suggests that report length is determined by supply (demand) of information by analysts (from investors).

The study then examines the implications of report length by investigating its association with forecast error and market reaction to analyst recommendations. The study finds that longer report is associated with a smaller forecast error, suggesting that a greater information amount tends to bring about more accurate information.

The positive association of longer reports with higher forecast accuracy is related with a stronger stock market reaction to both longer upgrade and downgrade reports. This relationship, however, might not be warranted due to investors' different credibility perception to these recommendation revisions, resulting in an asymmetric market reaction, i.e., (no) stronger reaction to longer upgrade (downgrade) reports.

In a related study, Hutton, Miller, and Skinner (2003) examine management earnings forecasts and hypothesize that bad news forecasts are always credible, whereas good news ones are optimistic and less credible.[1,2] Therefore, managers are able to increase the credibility of the latter by providing more verifiable information to help justify their optimistic opinions.

Motivated by the above study, I examine the information content of longer upgrades, documenting statistically and economically asymmetric market reaction to longer upgrades

[1] Hutton, Miller, and Skinner (2003) define forecast credibility as the extent to which investors believe the forecast and measure the credibility using the stock price reaction to the forecast.

[2] The analyst literature considers a sell recommendation highly credible due to analysts' incentives to issue optimistically biased reports, and often combines it with a hold recommendation. See footnote 13 for related information.

perceived to be less credible relative to downgrades of the same length. The credibility difference might be due to analysts' conflicts of interest and/or desire for access to management described above. To increase the credibility of upgrades, analysts are likely to justify their optimism by providing more detailed and relevant information (esp., on valuation), resulting in longer upgrades. Consequently, investors constantly show more positive reaction to longer credibility-enhanced upgrade reports, whereas they do not react as much negatively to equally lengthy downgrade reports inherently perceived to be credible.

In cross-sectional tests, market reaction to longer upgrades is more (less) pronounced when they have more cash flow discussion (tables), suggesting that investors are more sensitive to a valuation-specific narrative which is more beneficial than a non-narrative valuation summary in a table for the credibility enhancement of upgrades. Market also shows stronger reaction to longer upgrades by a less experienced, a busier, or a male analyst whose upgrades are perceived to be less credible. For the same reason, report length effect is more pronounced for a firm with higher information asymmetry or during greater uncertainty.

Different from report length (or amount), previous studies (e.g., Jacob, Lys, and Neale, 1999; Loh and Stultz, 2018) measure analysts' research effort in terms of forecast frequency. The research examines whether greater page length is associated with fewer subsequent revisions, finding their negative relationship.

Overall findings are robust to different measures of report length and recommendation (i.e., logarithm and levels, respectively), to the specifications with different fixed effects or additional controls, and to adjustments for standard errors using a different two-dimension clustering. Particularly, a within-bank analysis shows the robustness by controlling for more bank-specific characteristics.

The research makes several important contributions. First, the paper contributes to analysts' research effort literature by comprehensively studying research effort based on the number of pages in their reports and thus motivating and extending prior research (e.g., Loh and Stulz, 2018). Specifically, the study provides the justification of report length as a research effort measure by showing that longer upgrades have a positive association with market reaction. This highlights an important difference in motivation to issue longer reports between analysts and management. That is, analysts provide supplementary information to increase the credibility of optimistically-biased upgrades, whereas management supplies additional information to hide bad news: research credibility effort vs. information obfuscation motive. Thus, the paper also contributes to the annual report literature which finds 10-K filing length to be a proxy for readability or complexity. Taken together, the study motivates researchers to investigate the nature (or motivation) of other larger documents, contributing to the disclosure literature.

In addition, to identify various report length determinants, the study finds that longer reports are associated with a smaller forecast error, through which positively influences market reaction. The paper also shows how two research effort proxies (i.e., report length (or amount) and forecast frequency) are related. Thus, the research helps improve our understanding and measurement of the determinants of analysts' forecast performance by suggesting that controlling for report length (or its alternatives) in forecast research is meaningful, especially, for textual analysis.

The paper makes another contribution to the literature on analysts' optimism by showing that similar with management forecast, optimistically-biased favorable recommendations with more details become credible through accuracy, which are highly valued by investors. The research also contributes to the same literature by finding that analysts' optimistic-bias toward favorable opinions is more mitigated with additional details in valuation.

Lastly, there is a debate on measurement of forecast frequency as a proxy for research effort. Contrarily, report length is measured by simply counting the number of pages. Therefore, counting pages is more practical than measuring frequency for general report users to calculate research effort. Counting pages is especially helpful for unsophisticated investors who have difficulty in measuring forecast frequency due to the lack of data. This suggests the practical implication to use report length as a proxy for analyst effort.

This paper proceeds as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 explains the research design and the sample selection. Section 4 reports the main empirical analyses on the determinants and consequences of report length. Section 5 presents robustness checks. Section 6 describes the cross-sectional tests. Section 7 discusses the association between report length and forecast frequency. Section 8 concludes the paper.

2. Literature review on annual vs. analyst report length and Hypotheses development

2.1 Annual report (Form 10-K) length: proxy for complexity

Leuz and Schrand (2009) are the first to count the number of pages in the entire annual reports (i.e., Form 10-Ks) in 2001 as a proxy for a disclosure level. 10-K length by page count consists of Items 1 through 15 including the exhibits and financial statement schedules in Item 15. Using 10-K length, they find that the cost of capital shocks by the 2001 Enron scandal are positively associated with report length as a proxy for firms' disclosures in their subsequent annual 10-K filings.

In contrast, using its file size, Loughran and McDonald (2014) argue that page length of 10-K filings is a proxy for a readability level, not disclosure. The file size in megabytes is the sum of words, tables, pictures, graphics, and HTML code of complete submission text file from Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database of the U.S. Securities and Exchange Commission (SEC), suggesting that it is equivalent to the number of pages (i.e., page count). They find that possibly due to management's bad news obfuscation tendency, 10-K file size has a positive association with post-filing date abnormal return volatility, earnings surprises, and analyst forecast dispersion. This is inconsistent with Leuz and Schrand (2009)'s explanation that file size is a proxy for disclosure. They explain that if the alternative explanation is true, then "one would expect larger documents to be negatively (not positively) related to volatility and analyst dispersion". Thus, they suggest that file size (or page count) is a measure for readability, not disclosure in "any longer documents". However, their argument might be valid in 10-K filings, but thanks to the growth in textual analysis, it is found not to be true in other documents such as analyst reports.

Accepting the finding by Loughran and McDonald (2014), Li and Zhaoz (2016) further find that 10-K file size proxies both readability and information content. They argue that larger 10-K flings have more informative materials about which take time for investors to learn due to lower readability (or higher complexity). Comparing with 10-K reports, they argue that earnings announcements tend to be shorter and less complex and are associated with a decrease in uncertainty in a short horizon. This also suggests that other larger documents such as analyst reports might carry information more than complexity, which leads to investors' positive reaction.

2.2 Analyst report length: proxy for analyst research effort

Counting the number of pages in analyst reports from Morgan Stanley, Loh and Stulz (2018) measure report length as a proxy for analysts' research effort (or information amount).

Before report length, analysts' forecast frequency (i.e., activity) is commonly used to measure their forecast effort. For example, Jacob, Lys, and Neale (1999) define forecast frequency as the number of earnings forecasts that analysts make for a specific firm in a specific year (i.e., individual analyst's firm-specific forecast effort), arguing that the higher forecast frequency, the more forecast effort to the firm.

On the other hand, Barth, Kasznik, and McNichols (2001) measure forecast effort as the negative of the average number of firms covered by the firm's analysts, calculated as -1 times the sum of the number of firms followed by a firm's analysts in a particular year divided by the number of analysts covering the firm in that year (i.e., all analysts' firm-specific forecast effort). They interpret a less number of total firms that a specific firm's analysts follow as more effort to cover the firm.

Klettke, Homburg, and Gell (2015), however, argue that the first measure is not sufficient because the commonly applied firm-specific measure of forecast effort does not consider general analyst behavior for all covered firms. Additionally, by pointing out that the second measure is equal for all analysts covering the firm, they introduce a measure for general forecast effort by each analyst individually (i.e., individual analyst's general (or non-firm-specific) forecast effort). Specifically, they calculate the average number of forecasts that an analyst issues for all covered firms, excluding the covered firm in a particular year. Consistent with other research based on forecast frequency, their findings show its negative relationship with forecast error.[3]

Compared to forecast frequency, report length by page count (or information amount) can be another proxy for analyst' firm-specific research effort since it measures their individual overall research effort on collecting, analyzing, and presenting all information relevant to their

[3] Untabulated findings show that forecast frequency is not related with forecast accuracy.

investment opinions. In addition, report length is different from report readability in that the latter is differently measured and does not contain non-narrative information as part of analysts' overall research effort, even though it is sometimes referred to as the same name. For instance, following Li (2008) on annual report readability, De Franco, Hope, Vyas, and Zhou (2015) measure analyst report readability using the number of words and the number of characters. Similarly, Huang, Zang, and Zheng (2014) calculate the estimated residual or the number of sentences to measure analyst report readability. They argue that longer reports are more difficult to read and process for the users.[4]

Recently, researchers use report length as a proxy for an individual analyst's firm-specific research effort. Specifically, counting the number of pages of analyst reports from a single investment bank, Morgan Stanley, Loh and Stulz (2018) measure report length to capture research effort. They only document that report length, as a dependent variable, is positively related with bad times, e.g., a global financial crisis or recessions. Overall, they show that greater report length is associated with better and more information, reflecting more research effort.

Earlier, using spin-off firms, Feldman, Gilson, and Villalonga measure the amount of *attention* that analysts devote to their covered firms in their working paper (2010).[5] As an independent variable, they also use both the total number of pages and the proportion of pages devoted to analyzing either the parent or subsidiary. They find that analysts issue more accurate forecasts on a parent firm rather than a subsidiary as they devote more effort to the former by including more detail in the forecasts.

---

[4] 10-K file size proxies readability (Loughran and McDonald, 2014), whereas it proxies both readability and information content (Li and Zhaoz, 2016). See Section 2.1 for more details.
[5] Feldman, Gilson, and Villalonga examine page length variable in their working paper (2010), but exclude it from Strategic Management Journal (2014). Thus, Loh and Stulz are the first to accept report length as analysts' research effort in a peer-reviewed journal (Journal of Finance, 2018), but without its justification for the research effort.

Even though both studies use report length, they do not provide justification for it as a valid proxy for research effort. However, using machine-learning approach on stand-alone CSR reports, Clarkson, Ponn, Richardson, Rudzicz, Tsang, and Wang (2018) document a positive association between CSR performance and CSR report length (i.e., disclosure level) measured by the number of words and sentences, suggesting that linguistic features can predict good or bad CSR performance firms, as predicted by signaling theory rather than legitimacy theory.

Using report length based on a larger sample size without the limitation to a firm-specific situation, the paper fills the gap by providing empirical evidence that analysts *signal* their overall research effort through report length.

Analysts' primary responsibility is to forecast the value of the firm they cover. Their forecasts significantly differ in accuracy depending on known factors, i.e., control variables in the models such as brokerage-, analyst-, and firm-specific characteristics.

Using forecast frequency as a proxy for analysts' forecast effort, prior studies show that all else equal, analysts who devote higher forecast effort are more accurate than those who devote lower effort (e.g., Jacob, Lys, and Neale, 1999). Measuring the same construct differently, Loh and Stulz (2018) suggest that report length is another proxy for research effort. However, one argues that longer reports do not necessarily increase forecast accuracy because information amount and accuracy are different constructs. Nevertheless, following Loh and Stulz (2018)'s argument of the positive association between longer reports and better information, I expect that report length reduces forecast error as shown in forecast frequency. Accordingly, I set forth the first hypothesis as follows:

Hypothesis 1: Ceteris paribus, length and error of earnings forecasts are negatively associated.

2.3 Credibility-enhancing hypothesis

If longer reports are positively associated with higher forecast accuracy, then it can be expected that stock markets react more positively to both longer upgrade and downgrade reports. This expectation, however, might be unwarranted due to investors' different credibility level to these stock recommendation revisions, resulting in an asymmetric market reaction, i.e., (no) stronger reaction to longer upgrade (downgrade) reports.

Using an experiment based on psychological theories, Hirst, Koonce, and Simko (1995) find that when an analyst report conveys unfavorable information, subjects are more likely to seek out other information in the report because an unfavorable one is contrary to their expectation that analysts issue a favorable one. In contrast, Francis and Soffer (1997) document that investors place greater weight on other information in an analyst report when the report contains a favorable recommendation than when it includes an unfavorable one because the former is inherently perceived to be biased. They explain that due to their optimism from the conflicts of interest (e.g., current and/or potential investment banking business or trading commissions) and/or their motive to gain access to management as a source of information, analysts are reluctant to issue an unfavorable recommendation.

Using management earnings forecasts, Hutton, Miller, and Skinner (2003) show that bad news forecasts are always credible, whereas good news forecasts are less credible. Thus, managers increase the credibility of good news forecasts by supplementing them with verifiable forward-looking statements about earnings components to justify their earnings optimism, which market favorably reacts to.

In analyst forecasts, buy (sell) recommendation is good (bad) news. Similarly, upward (downward) recommendation revisions (or changes) mean good (bad) news. Previous studies (e.g., Womack, 1996; Jagadeesh, Kim, Krische and Lee, 2004) document that revisions convey new and useful firm-specific information. Moreover, prior research (e.g., Boni and Womack 2006; Jegadeesh and Kim, 2010) confirms that recommendation changes are more informative than mere levels such as buy and sell. This suggests that a change in analysts' previous belief in their covering firms better reflects their research effort than levels. Especially, due to analysts' conflicts of interest and/or motivation for access to management (e.g., Hirst, Koonce, and Simko, 1995; Francis and Soffer, 1997; Michaely and Womack, 1999; Ke and Yu, 2006; Ljungqvist, Marston, Starks, Wei, and Yan, 2007), analysts tend to initially write favorable level recommendations (i.e., buy/hold) perceived to be less credible by investors. Because favorable levels outnumber unfavorable ones, it is less likely for analysts to revise the former upwardly than downwardly, resulting in fewer upgrades than downgrades. Nevertheless, if analysts make upgrades, then the credibility of upgrades will be much less credible than favorable levels. Thus, I focus on recommendation revisions for a complete understanding of report length for research effort.

In sum, upgrades are perceived to be less credible than downgrades because they are optimistically biased possibly due to well-documented analysts' conflicts of interest and/or motivation for access to management. Particularly, Conrad, Cornell, Landsman, and Rountree (2006) find that analysts tend to issue upgrades more than downgrades if their brokerage firm has a historical investment banking relationship with the firm they cover. As shown in management behavior on good news, to increase the credibility of these favorable recommendations, analysts tend to justify the optimistically-biased favorable ratings by providing more detailed and useful information (esp., valuation-specific detail), resulting in a long report, i.e., bigger research effort. Thus, investors react more positively to longer credibility-enhanced upgrade reports, whereas they do not show a stronger negative reaction to downgrade reports of equal length because they are already credible and their additional information might be qualitative soft-talk not related to valuation, i.e., not informative. This prediction leads to the following hypothesis.

Hypothesis 2: Ceteris paribus, stock market reacts more strongly to longer upgrade reports than downgrade reports of equal length.

3. Research methodology and sample selection

3.1 Measurement of report length

The research question of interest is whether report length is a valid proxy for analysts' research effort by examining its determents, and primarily, its association with forecast accuracy and/or informativeness. Without controlling for mechanical page variations due to regulatory and brokerage template requirements,[6] previous literature (Feldman, Gilson, and Villalonga, 2010; Loh and Stulz, 2018) measures research effort as the total number of pages (*page*) of the forecasts. Ranked by an investment bank and a report year to control for such page differences, therefore, report length in deciles (*pagedec*) is a better measure for research effort than a raw number of pages (*page*). I treat *pagedec* as a continuous variable because the ranked pages are equally divided into 10 parts and thus, the numerical distance between each set of subsequent categories can be assumed equal (or even). Thus, *pagedec* is the variable of interest as a proxy for research effort.

For the robustness checks, the logarithm (*logpage*) of a raw number of pages is employed since its distribution is highly skewed to the right. In untabulated tests, two more measures are

[6] In 2002, the U.S. Congress enacts the Section 501 mandate of the Sarbanes-Oxley Act (SOX) governing research analysts' conflicts of interest. Subsequently, the New York Stock Exchange (NYSE) amends its Rule 351 (Reporting Requirements) and Rule 472 (Communications with the Public) while the National Association of Securities Dealers (NASD) releases Rule 2711 (Research Analysts and Research Reports). The historic Global Settlement with 10 of the U.S. largest investment banks is announced in December 2002 based on the enforcement actions against the issues of the conflicts of interest related to their analysts' recommendations. In 2003, the SEC, NYSE, and NASD, and the banks reach the settlement resulting in nearly $1.4 billion dollars of fines and penalties and reinforce the structural reforms on NYSE Rule 472 and NASD Rule 2711. The new rules intend to make research output more credible by establishing stringent disclosure requirements.

tested: both a quintile of a raw number of pages and an abnormal page length equal to estimated residuals from regressing a raw number of pages on control variables in Equation (2) below. Their results are qualitatively similar to those of *pagedsec* and its alternative, *logpage*.

3.2 Measurement of earnings forecast error and informativeness

Loh and Stultz (2018) suggest that a longer report (i.e., more information) has better information. Thus, the paper exams the relationship between analysts' report length (*pagedec* and *logpage*) and their earnings forecast performance. Following Bae, Stulz, and Tan (2008), I define analysts' absolute forecast error in percentage as follows:

$$afeprcm_{i,j,t} = 100 \text{ x } |forecast_{i,j,t} - actual_{j,t}|/prcm_{j,t} \qquad (1)$$

where $afeprcm_{i,j,t}$ is the absolute forecast error for analyst i, following firm j for fiscal year t scaled by $price_{j,t}$ (i.e., the latest monthly stock price from Compustat), $forecast_{i,j,t}$ is the last one-year-ahead forecast of annual earnings of firm j for fiscal year t issued by analyst i, and $actual_{j,t}$ is the actual annual earnings for firm j for fiscal year t. Depending on the scalers such as $actual_{j,t}$, and $forecast_{i,j,t}$ of firm j for fiscal year t, alternative measures are labeled as $afeact_{i,j,t}$ and $afeeps_{i,j,t}$ (e.g., Hong and Kubik, 2003).[7] Earnings forecasts and actual earnings are from I/B/E/S. The higher the absolute forecast error, the lower the forecast accuracy.

To test whether longer report increases the informativeness of analyst recommendations, we measure the cumulative abnormal return (*car5*) as the sum of daily market-adjusted abnormal return during five days [-1, +3] starting from one day before an analyst forecast date. Analyst forecast dates are captured from the report per se downloaded from Investext. The daily stock return is based on the holding period return from CRSP and the market return is the daily value-weighted return including all distributions of U.S. stocks from CRSP.

[7] Dividing by the share price, actual earnings, and earnings forecasts makes it possible to compare forecast errors across time and across firms.

3.3 Regression specification

I separately regress the dependent variables of error and informativeness of analysts' earnings forecasts on various report length variables proxied for research effort. I control for series of factors that might affect forecast accuracy and stock returns, including a year fixed effect to control for common time trends, and an industry (a bank) fixed effect to account for cross-industry (bank) differences. The baseline regression model is as follows:

$$dependent = \beta_0 + \beta_1 pagedec + \beta_2 \Sigma analyst + \beta_3 \Sigma firm + \beta_4 industy\ F.E. + \beta_5 bank\ F.E. + \beta_6 year\ F.E. + \varepsilon \quad (2)$$

where the main dependent variables (*dependent*) are the proxies for either absolute forecast error (*afeprcm*) in year *t* in a forecast model or cumulative abnormal returns (*car5*) in year *t* in a market reaction model. All the independent variables are measured in year *t-1* or year *t*. *page*, *at*, and *nanalyst* are log-transformed in all models due to their high skewness. The key variable of interest (*pagedec*) is a proxy for analysts' research effort level measured as the total number of forecast pages in deciles: its alternative is *logpage*. In a market reaction model, I additionally include the changes (*upgrade* and *downgrade*) of analyst recommendations as independent variables to test relative credibility-enhancement effect by comparing market reaction between two revisions. I also run an alternative market reaction model with firm, analyst, and year fixed effects. The coefficients on constants from the alternative model are not reported since Stata does not produce them. The rest of variables control for factors which influence dependent variables. Standard errors are cluster-adjusted at an analyst and a year (or firm) level. [8] Appendix A provides detailed variable definitions.

[8] Regardless of an alternative market model or a different clustering, the results are qualitatively similar.

I follow the previous literature to control for two sets (*Σanalyst* and *Σfirm*) of characteristics that affect forecast frequency, error, and investors' reaction to recommendations, i.e., analyst (including brokerage firm)- and firm-specific characteristics.

According to prior research (e.g., Clement, 1999; Rubin, Segal, and Segal, 2017), analyst characteristics can explain analyst performance such as forecast accuracy. Thus, I control for the following analyst (including brokerage house)-specific variables in both a forecast and market reaction model: analyst's experience following the firm (*firmexp*) and the industry (*indexp*) measured as the number of years the analyst covers the firm (industry) as of year *t*; analyst's busyness (or task complexity) calculated as the number of firms (*firmcover*) and industries (*indcover*) covered by the analyst in year *t*; resources of the brokerage house (*brsize*) defined as the number of analysts employed by the brokerage firm employing the analyst in year *t*. Clement (1999) finds that forecasts made closer to earnings announcements are more accurate. Thus, I control for forecast uncertainty (*horizon*) calculated as the number of days from the forecast date to fiscal year-end since a longer time period between the dates increases forecast error (Richardson, Teoh, and Wysocki, 2004). Similarly, I control for information uncertainty measured as previous forecast dispersion (*displag*) defined as the standard deviation of earnings forecasts divided by the absolute value of their mean in year *t-1*. Gu and Wu (2003) and Zhang (2006) find that it is negatively correlated with forecast accuracy. Following Loh and Stultz (2018), I also include previous forecast error (*afeprcmlag*). In a market reaction model, I control for report readability (*readability*) from De Franco, Hope, Vyas, and Zhou (2015), but drop *afeprcmlag* and *displag* which include for robustness check.

I then control for proxies for firm's financial and operating risk, as well as the information environment. These firm-specific variables are included in both a forecast and market reaction model. Specifically, I control for a firm's growth opportunities based on its market value (*mb*) calculated as a market value divided by a book value at year-end, its profitability (*roa*) in terms of a ratio of income before extraordinary items to total assets at the end of year *t*, its leverage (*leverage*) defined as total liabilities scaled by total assets at the end of year *t*, and its previous return volatility (*retstdpre1*) measured as the standard deviation of its daily stock return during one year prior to an analyst forecast date.

Finally, I also control for a firm's information environment by including its size (*logat*) measured as the natural logarithm of its total assets at year-end, an indicator variable (*loss*) equal to 1 if it has a negative earnings during three fiscal years before an analyst forecast, and 0 otherwise, and the number of analyst following (*lognanalyst*) calculated as the natural logarithm of the number of analysts following the firm in the previous year. Last but not least, I control for institutional holdings (*iholding*) measured as the total number of shares held by institutions divided by shares outstanding at the end of the same quarter in quarter *t*. All continuous variables are winsorized at 1 and 99 percentiles to reduce the effect of outliers.

3.4. Sample selection

To empirically test the hypotheses, I count the number of pages for each analyst report of the top 15 largest global investment banks based on total assets who cover U.S. firms. The reports are downloaded from Investext over 2000-2014. The report data then merges analyst and management forecast data from I/B/E/S, financial data from Compustat, and stock price data from CRSP. Some banks' reports in pdf file are not available in Investext, for example, Goldman Saches & Co. and Bank of America Securities LLC. Likewise, some banks' forecast data is not available in I/B/E/S. These unmatched banks are dropped from a sample. There are four U.S. investment banks (i.e., J.P. Morgan, Morgan Stanley, Citigroup, and Jeffries Co.) and three

European banks (i.e., Credit Suisse, Deutsche Bank, and UBS). See Table 2, Panel B for the bank distribution. The sample consists of 470,075 firm-analyst-date observations. After deleting missing values of variables in a forecast regression, the final sample contains 351,629 reports from 7 unique banks for 15 years, 1,806 unique analysts, 3,879 unique firms, and 24 industries.

4. Empirical results

4.1 Descriptive statistics

Table 1, Panel A, provides the descriptive statistics for main variables. In the sample, the mean value of *page* is 8.538 with a minimum of 2 and a maximum of 29, meaning that on average, each analyst forecast has about 8 and a half pages including a required disclosure section. Using Morgan Stanley reports, Loh and Stultz (2018) find that the average report length is 10.237 pages.[9] The mean value of a key report length (*pagedec*) is 5.460 with a median of 5.

As for the variables in a forecast error model, the mean value of *afeprcm* is 1.650. This suggests that on average, analysts are more likely to make an error on their forecasts by 1.650% of the latest monthly stock price of a firm.

Meanwhile, the mean value of cumulative abnormal return (*car5*) is -1.710%, suggesting that sample firms' stocks underperform a benchmark around analyst forecast release dates by 1.71%. The mean values of upward recommendation revisions (*upgrade*) and downward revisions (*downgrade*) are 0.044 and 0.046, respectively. This suggests that recommendation reiterations overwhelmingly account for revisions by 91%. Buy (sell) recommendations consist of about 54% (7%) of all forecasts. Consistent with previous literature, analysts are highly likely to issue significantly more buy than sell, but slightly more downgrade than upgrade since they tend to be overly optimistic in the first place.

---

[9] Huang, Zang, and Zheng (2014) report an average of 7.7 pages excluding brokerage disclosure sentences in the report.

Panel A of Table 2 reports the sample distribution by year during 2000-2014. Consistent with Loh and Stultz (2018), analysts devote more forecast effort (*pagedec*) during bad times (i.e., 2007-2009 credit crisis) due to higher information demand from investors concerned about the stock market uncertainty.[10] Especially, *pagedec* reaches the highest level of 5.620 in 2002 because of Sarbanes-Oxley Act (SOX), the New York Stock Exchange (NYSE), and the National Association of Securities Dealers (NASD) Rules on the disclosure of analysts' conflict of interest in their reports. The rules increase upgrade (but reduce buy in untabulated results) which is associated with more discussion on cash flow (*cf*). Generally, forecast error (*afeprcm*) decreases when *pagedec* increases. *table* constantly increases over time while *cf* is stable since 2004, suggesting that the difference between non-narratives and narratives gets bigger.

Untabulated results show the distribution of the sample by 24 industry groups in terms of the Global Industry Classification Standard (GICS) codes. Software & Services, Media, and Household & Personal Products are top 3 industries in average page length in decile, whereas Real Estate has the lowest, suggesting a shorter report for a firm with a higher tangible asset.

Table 3 displays the Pearson correlation matrix. Report length (*pagedec*) is significantly and positively associated with *upgrade*, whose relationship is twice that with *downgrade*. This provides initial evidence of analysts' research effort on improving the credibility of their upgrade perceived to be overly optimistic. In contrast, *pagedec* is significantly and negatively correlated with forecast error (*afeprcm*), suggesting that the more research effort, the less forecast error. *pagedec* is significantly positively correlated with valuation detail in a cash flow (*cf*) and with earnings management (*em*), whereas negatively associated with analyst characteristics (*firmexp and female*). This suggests that analysts tend to provide more information on cash flow details

[10] The National Bureau of Economic Research (NBER) reports that the recession periods are from March 15th, 2001 to November 15th, 2001, and from December 15th, 2007 to June 15th, 2009.

directly related to firm valuation or for a firm with greater earnings management, and when they are a rookie or a male. *pagedec* is mechanically positively correlated with the number of tables (*table*). *cf* and *table* have a positive association, suggesting that cash flow details accompany tables. The key variable, *pagedec*, generally has a similar correlation pattern with *page*. However, *indcover* (*crisis*) is significantly positively (negatively) associated with *page*, rather than *pagedec*, suggesting that analysts tend to issue a longer report when they are busy or during a financial crisis.

4.2 Univariate test

Table 4, Panel A, displays the mean comparisons of main variables by pages in deciles, i.e., *pagedec*. As analysts' effort increases from the first (i.e., D1) to the tenth (i.e., D10) decile, incremental change in *upgrade* is greater than that in *downgrade*, suggesting another initial evidence of analysts' effort on the favorable forecast credibility. The values of a forecast error variable (i.e., *afeprcm*) significantly drop as *pagedec* increases, suggesting initial evidence that the more research effort, the less forecast error. Meanwhile, Panel A of Table 4 shows that the decile values of *firmexp*, *em*, and *crisis* have outliers in D1 or D10, displaying polynomial (i.e., not consistent change) relationship with *pagedec*, and thus, their D1 and D10 comparisons for main variables are misleading. Using the median values of a raw number of pages (*pagedum*), Panel B of Table 4 shows more meaningful association between low and high report length, and main variables. An observation greater (smaller) than *pagedum* is treated as high (low). In general, the results of Table 4 are consistent with those of the correlation in Table 3.

4.3 Main regression analyses

In this section, I identify the determinants of a main independent variable (*pagedec*) and then investigate its consequences using the multiple OLS regression model specified in Section

3. For a robustness check, all main tables include alternative measures of both a main independent and dependent variable.

4.3.1 Determinants of report length

In this section, based on the supply and demand of information, I investigate forecast signal, analyst, and firm characteristics influencing report length by regressing *pagedec* on these. First, I start with the variables related to the supply of information by analysts. Due to an analysts' optimistic bias possibly from their conflicts of interest and/or motive on gaining access to management for better information (e.g., Hirst, Koonce, and Simko, 1995; Francis and Soffer, 1997; Michaely and Womack, 1999; Ke and Yu, 2006; Ljungqvist, Marston, Starks, Wei, and Yan, 2007), a favorable recommendation is perceived to be less credible relative to an unfavorable one.[11] Especially, Conrad, Cornell, Landsman, and Rountree (2006) find that analysts are more likely to issue upgrades than downgrades if their brokerage firm has a historical investment banking relationship with the firm they cover. To enhance the credibility of the former, analysts are likely to supply detailed supplementary information, resulting in a longer recommendation. See more about this in Section 4.3.4. Consistent with the prediction, Column (2), (4). (6), and (8) of Table 5 displays the findings that *upgrade* is more positively associated with *pagedec* than *downgrade*. In addition, report length is positively associated with an analyst's team (*team*). Report length also has a more positive relation with forecasts (*postearn*) issued after a firm's earnings announcements than with those (*preearn*) before the announcements because of more information available after the events.

On the demand side, report length is negatively related with a firm's previous return volatility (*retstdpre1*) because costs required to follow the firm (e.g., information process)

[11] The analyst literature often combines a hold and a sell recommendation as a sell recommendation, suggesting that the former is considered as much credible as the latter. See footnote 4 for related information.

outweigh benefits (e.g., trading commissions) from investors' high information demand on the firm. On the other hand, report length is positively associated with bad times (*crisis* or *recession*) such as financial crisis or recession due to investors' higher motivation for uncertainty reduction. The results are consistent with Loh and Stultz (2018)'s findings.

More importantly, the positive association between report length and readability (i.e., word length) suggests the mechanical relationship between these two, i.e., the longer the report is, the more non-narratives (e.g., tables) than narratives (e.g., words) the report has. In other words, a longer report is easier to read because of fewer words, inconsistent with the results from a longer 10-K report. Untabulated correlation results document the positive (negative) association between *readability* and *table* (*cf*) at the 1% level.

Overall, the findings are consistent with the notion that analyst report length increases with the expected supply (demand) of information by analysts (from investors).

4.3.2 Report length and earnings forecast accuracy

The results of Table 6 show the linear regression results of report length on earnings forecast error. Except for 4 out of all 12 models, the coefficients on *pagedec* and *logpage* are significantly negative, implying that greater research effort tends to induce less forecast error. Consistent with the first hypothesis, this suggests that the information amount of analyst reports improve their quality in terms of accuracy.

In untabulated analyses, I re-estimate the forecast accuracy test including firm fixed effect instead of industry fixed effect. I also rerun the test after replacing bank fixed effect with analyst fixed effect. In addition, using a firm, analyst, and year level, I test other combinations of two-way clustering to adjust for standard error. No inferences are affected by these alternative specifications.

As for control variables, if analysts have a longer horizon to forecast (*horizon*), then they are likely to have more error in their forecasts. Similarly, if they cover highly leveraged (*leverage*), more previously volatile (*retstdpre1*) firms, or have greater previous forecast error/dispersion (*afeprcmlag, afeactlag, or afeepslag /displag)*, they tend to make more forecast error. On the contrary, their forecast error is likely to decrease when analysts have more industry expertise (*indexp*) or cover higher growth/profitable firms (*mb*/*roa*).

4.3.3 Report length and stock recommendation informativeness

It is well documented that favorable recommendations are perceived to be less credible relative to unfavorable ones since they are optimistically biased especially due to analysts' conflicts of interest and/or motivation to gain access to management for better information (e.g., Hirst, Koonce, and Simko, 1995; Francis and Soffer, 1997; Michaely and Womack, 1999; Ke and Yu, 2006; Ljungqvist, Marston, Starks, Wei, and Yan, 2007). To enhance the credibility of the former, analysts are likely to justify their optimistic opinions by providing more detailed information, resulting in an increase in the overall amount of information, i.e., a longer report. As a result, investors strongly react to a longer favorable report, whereas they do not show as much strong reaction to an unfavorable report of equal length inherently perceived to be credible by them. Note that as in Table 5, reports with favorable investment advice (i.e., *upgrade*) are more positively associated with page length than unfavorable ones, suggesting initial evidence that analysts exert efforts on improving the credibility of an upgrade by adding more detailed information.

Panel A of Table 7 displays asymmetric market reaction by showing that relative to a baseline upgrade, investors constantly react more strongly to a longer upgrade report (*upgrade*pagedec* (or *logpage*)), whereas relative to a baseline downgrade, they do not show constantly stronger reaction to a longer downgrade report (*downgrade*pagedec* (or *logpage*)). In other words, a longer upgrade has a stronger market reaction than a downgrade in the same length. Specifically, the coefficients on upgrade* *pagedec* (or *logpage*) are statistically positive across all the models except one, whereas those on downgrade**pagedec* (or *logpage*) are not significant at all, significantly positive or negative, i.e., not consistently negative.[12] This supports the prediction that *ceteris paribus*, stock market shows a stronger reaction to a longer report with favorable recommendations than that with pessimistic opinions.

More importantly, for specifications where the sum of the coefficients on *pagedec* and *upgrade***pagedec* is significantly different from zero, I also report the economic significance of the effect of *pagedec* for an upgrade. Specifically, Panel B of Table 7 indicates that a one standard deviation increase in *pagedec* (*logpage*) when a forecast is an upgrade improves *car5* by 13.58% (9.32%) on average, or about 7.94% (7.67%) of the mean *car5* on average. 13.58% is economically important given that the average annualized total return for the S&P 500 index over the past 90 years is 9.8%. Overall results suggest the statistical and economic significance of analysts' research effort component effect of an upgrade report if all the other variables are at a fixed value.

As for analysts' signals, cumulative abnormal returns (*car5*) is positively associated with *upgrade* across models except two, whereas *car5* is significantly negatively with *downgrade* across models, suggesting that *downgrade* is more credible and thus informative than *upgrade*. As for control variables specific to analysts, *car5* has a positive relationship with industry experience (*indexp*), whereas it is negatively correlated with their firm experience (*firmexp*) and their report readability (*readability*), suggesting that industry expertise is more valuable for

[12] The results are qualitatively similar after adjusting for standard errors using firm-year clustering.

investors and easy-to-reports do not give information advantage to them. In terms of firm-specific control variables, *car5* is negatively related to most of them, e.g., *lognanalyst*, suggesting no information advantage to investors.

Overall, the results provide robust evidence of a stronger market reaction to a longer upgrade. In other words, by providing more information, analysts make a significant credibility-enhancing effort on upgrade perceived to be less credible relative to that with a downgrade. Considering the significantly positive association between report length and forecast accuracy, this suggests that a longer upgrade becomes credible because of its informativeness through its accuracy.

5. Robustness checks

In this section, using a recommendation level, a within-bank analysis, and an extended model with more controls, I implement robustness tests on the results of Table 7. [13] For brevity, only the coefficients on key variables are reported.

5.1 Recommendation levels: buy and sell

Using recommendation levels, i.e., *buy* and *sell*, Panel C of Table 8 replicates the results of Column (1), (3), (5), and (7) of Table 7 and shows that the coefficients on the main interaction term, *buy* pagedec* are significantly positive across model, confirming the results of Table 7 in terms of main interaction term. More importantly, Column (1) and (2) of Panel A of Table 8 indicates that one standard deviation increase in *pagedec* increases *car5* by 7.72% (6.19%), or about 4.52% (3.62%) of the average *car5*. Overall, the results suggest that holding other things constant, the statistical and economic importance of research component effect of a buy report on market reaction is substantive.

[13] The results are qualitatively similar after adjusting for standard errors using firm-year clustering.

Using within-firm-year and within-analyst-year subsample, untabulated tests show the results similar to those of Table 7. Overall, the robust tests support the credibility-enhancing hypothesis on a longer upgrade report.[14]

5.2 Within-bank analysis

To control for bank-specific characteristics, I use a report length decile and also include a bank fixed effect in every model. Nevertheless, each investment bank has a different amount of the required disclosure at the end of a research report. To control for this, I replicate the results of Column (2) of Table 7 for each investment bank. Table 8, Panel B, reports the results of the within-bank market reaction analysis using *logpage* as a main report length proxy. Panel B of Table 8 shows that the coefficients on the interaction term, *upgrade*logpage* are significantly positive in four out of seven banks, confirming the results of Table 7.[15] Using *pagedec* as its alternative, the results remain unchanged.

5.3 Extended market reaction model

Replicating the results of Column (1) and (3) of Table 7, Panel C of Table 8 shows the results of the extended market reaction model including seven additional control variables from both the determinant and forecast error model, i.e., *team*, *preearn*, *postearn*, *crisis*, *recession*, *afeprcmlag*, and *displag*. Panel C of Table 8 displays that the coefficients on *upgrade* pagedec* are significant across models, confirming the results of Table 7. Using *logpage* as its alternative, the results are qualitatively similar. Consistent with Chen, Cheng, and Lo (2010), *preearn* is more positively associated with *car5* than *postearn* because analysts' earnings forecasts are more

[14] The disclosure rules on analyst conflicts of interest in 2002 increase report length, but the increase does not reflect analysts' research effort. To control for the disclosure variation between before and after the regulations, I exclude report length variables before 2003, and find that market reaction to a longer report with upgrade are still positively significant. This suggests that report length is a valid proxy for research effort.

[15] Column (14) of Panel B of Table 8 excludes an industry fixed effect due to its multicollinearity with *pagedec*.

informative before a firm's earnings announcements than after. Note that the coefficients on *crisis* have a different sign depending on fixed effects, suggesting that a firm-analyst-year fixed effect model is inferior over an industry-bank-year fixed effect model because *crisis* is highly likely to be negatively associated with *car5*.

6. Cross-sectional test on market reaction to longer revisions

So far, the paper shows that 1) an upgrade tends to have more information, 2) a longer upgrade is positively associated with accuracy, and 3) a longer upgrade tends to be more informative because it provides more accurate information.

In this section, I cross-sectionally investigate the influence of detailed information, analyst, and information environment traits on report length effect. For this, I rank each trait by a brokerage firm and a forecast year and partition them into two groups by median values. High (low) indicates when the value of each trait is above (below) its median. Yes (no) indicates when the trait (does not) exist(s). The key interaction term of interest is *upgrade***pagedec* (or *logpage*). Only the coefficients on key variables are reported for brevity.

6.1 Detailed information traits

The results suggest that analysts exert efforts on improving the credibility of an upgrade by adding more detailed information. Then, the question is what kind of details are, i.e., narratives or not. To examine the moderating effect of details on relative market reaction to a longer revision, I create a variable to capture non-narrative valuation summary, *table*, by counting the number of tables. Tables usually contain the covered firm's comparative financial or valuation summary in terms of previous, current, and future results. *table* is mechanically positively correlated with report length. I expect that report length effect is more pronounced for a longer upgrade with a fewer number of tables because tables are in less detail and are not directly related with valuation, but is more likely a presentation of narratives.

Column (1) to (4) of Panel A of Table 9 shows the results on how the number of tables influences the results of Column (1) and (2) of Table 7. Specifically, the coefficients on *upgrade*pagedec* in a low table group (i.e. low) are greater than those in a high group (i.e., high) even though the coefficients are not statistically different at the 10% level (*Z*-test=-0.784). However, the coefficients *upgrade*logpage* are statistically different at the 10% level (*Z*-test=-1.931), suggesting that fewer non-narratives generally have stronger report length effect than more non-narratives, consistent with the prediction.

If a page of the report has fewer non-narratives, e.g., a fewer number of tables, one would expect more narratives. Then, another question is whether the market reaction is more pronounced for a longer upgrade report with more valuation narratives on the covered firm. To address this, I create a narrative valuation-specific variable for *cf*, calculated as the ratio of the number of cash flow keywords to the total number of words. Untabulated results show that 38.99% of the reports contain cash flow keywords (*cf*) which are positively related with a longer report. I expect that report length effect is greater for a longer upgrade with more valuation-related narratives (*cf*) on the covered firm's cash flow.

The results of Column (5) to (8) of Panel A of Table 9 are consistent with the hypothesis by showing that the coefficients on *upgrade*pagedec* in a high cash flow group (i.e. high) are statistically bigger than those in a low group (i.e., low) at the 10% level (*Z*-test=1.870). However, the coefficients on *upgrade*logpage* are not statistically different at the 10% level (*Z*-test-0.574). Overall, this suggests that in general, additional discussion on a cash flow is more useful to enhance the credibility of an upgrade, whereas additional details on non-narrative valuation summary are relatively less useful. In other words, investors are more sensitive to more valuation-specific discussion than to a financial or valuation summary in a table.

6.2 Analyst characteristics

Analyst's characteristics influence the credibility of upgrade perceived to be less credible and thus, market reaction. For example, investors are less likely to trust an upgrade issued by a less experienced analyst and a busier analyst. Thus, I expect that to increase the credibility of an upgrade from a rookie, she/he tends to provide more information, resulting in a longer upgrade and thus, stronger positive market reaction. Panel B of Table 9 shows the results. high (low) indicates when the median values of an analyst's firm experience level on the covered firm (*firmexp*) or busyness level measured as the number of the covered industries (*indcover*) are above (less) its median.

Specifically, Column (1) to (4) of Panel B of Table 9 reports the results consistent with the experience prediction by showing that the coefficients on *upgrade*pagedec* (*upgrade*logpage*) in a low experienced group are significantly negative and greater than those in a high experienced group at the 10% (5%) level. On the other hand, the results of Column (5) to (8) of Panel B of Table 9 also support the busyness hypothesis because the coefficients on *upgrade*pagedec* (*upgrade*logpage*) in a high busy group are significantly positive and bigger than those in a low busy group at the 10% level (marginally).

Column (9) to (12) of Panel B of Table 9 reports the results of another analyst characteristic using an indicator variable where an analyst is a female (*female*). yes (no) indicates when the report is issued by a female (male) analyst. Kumar (2010) finds that a female stock analyst issues more accurate forecasts than a male one, suggesting that her upgrade is more credible than a male's. Thus, I expect less (more) report length effect in a female (male) group.

The results of Column (9) to (12) of Panel B of Table 9 are consistent with the prediction by showing that the coefficients on *upgrade*pagedec* (*upgrade*logpage*) in a male group (i.e., no) are significantly negative and greater than those in a female group at the 10% level (marginally).

6.3 Information environment effect

Panel C of Table 9 examines the moderating effect of information environment across firms, i.e., information asymmetry (*em*) or uncertainty (*crisis*). *em* is a continuous variable for earnings management level, measured as discretionary accruals by Modified Jones Model, whereas *crisis* is an indicator for the global financial crisis between 2007 and 2009. high (low) indicates when the value of information asymmetry (em) is above (below) its median. yes (no) indicates when information uncertainty (crisis) (does not) exit(s).

I expect that analysts tend to make upgrade longer by providing more details since the upgrade for a firm with greater discretionary accruals is less credible to investors. The results of Column (1) to (4) of Panel C of Table 9 are consistent with the prediction by showing that the coefficients on *upgrade*pagedec* (*upgrade*logpage*) in a high information asymmetric group are significantly positive and bigger than those in a low information asymmetric group at the 5% level (marginally).

Meanwhile, Loh and Stulz (2018) suggest that analysts work harder by supplying more information in response to a higher information demand from investors during bad times such as a financial crisis, resulting in a longer report. Accordingly, I predict that positive market reaction to a longer upgrade is more pronounced during the crisis. Column (5) to (8) of Panel C of Table 9 confirms this hypothesis by showing that the coefficients on *upgrade*logpage* (*upgrade*pagedec*) during the crisis (i.e., yes) are significantly positive and bigger than those during no crisis (i.e., no) at the 1% level (marginally). Note that compared to the tests on analyst traits, those on *em* might suffer more from the endogeneity issue because the firm characteristic might be greater influenced by the stock market.

7. Report length and forecast frequency

Report length and forecast measure analysts' research effort in a different way, i.e., how much information analysts discuss in their reports vs. how often analysts revise their reports. Thus, it is natural to examine the relationship between the information amount and frequency of an analyst research report. Specifically, following the definition of commonly-used forecast frequency (e.g., Jacob, Lys, and Neale, 1999; Loh and Stultz, 2018), the study is able to compare two measures for an individual analyst's firm-specific research effort. I predict that report length and forecast frequency are negatively related because analysts are less likely to revise forecasts once they are confident that their forecasts are accurate because of more detailed information, i.e., higher research effort proxied by longer forecasts (e.g., Klettke, Homburg, and Gell, 2015).

Following the baseline model in Equation (2), the dependent variable is the number of analyst forecasts (*freq*), calculated at the firm-analyst-year level. Control variables are the same with those of Table 5 and *retstdpre1*. For a consistent unit of analysis, both report length and control variables (i.e., *horizon* and *iholding*) are the averages within firm-analyst-year. The key independent variables are *pagedecmn* and *logpagemn*.

Table 10 reports the linear regression results of report length on forecast frequency which is a measure for research effort (e.g., Jacob, Lys, and Neale, 1999), and shows that the coefficient on *pagedecmn* and *logpagemn* are significantly negative across models.[16] This suggests that report length and forecast frequency are negatively related, consistent with the

[16] The results remain unchanged adding more controls from Panel B of Table 8, using quintile or residuals of pages, or adjusting for standard errors using firm-year (or analyst) clustering.

hypothesis. In other words, if analysts make a greater effort on a forecast, then it is less likely to revise it later.

8. Conclusion

Prior studies (e.g., Loughran and McDonald, 2014) find that management uses longer 10-K filings to obfuscate bad news. Contrarily, analysts write longer reports in response to investors' information need in heightened uncertainty (Loh and Stulz, 2018) or their own needs (Feldman, Gilson, and Villalonga, 2010).

Counting the number of pages in the analyst reports only from Morgan Stanley, Loh and Stulz (2018) measure analysts' research effort, and only find that report length is positively associated with bad times such as a global financial crisis or recessions. In a spin-off setting, Feldman, Gilson, and Villalonga (2010) also measure page length proxied for analysts' *attention* to their covered firms. Their findings are crucial to motivate the study because they provide a clear motivation distinction between *analyst* report and *annual* report length. In other words, analysts issue a longer research report to provide additional useful information, while management writes a longer annual report to hide disclosed bad information. However, both studies do not justify or motivate the use of report length as a proxy for analysts' research effort.

On the other hand, using signaling theory, Clarkson, Ponn, Richardson, Rudzicz, Tsang, and Wang (2018) find a positive association between CSR performance and CSR report length measured by the number of words and sentences in stand-alone CSR reports. This suggests that analysts *signal* their overall research effort through report length.

The paper fills the gap by comprehensively investigating both the determinants and the consequences of report length. Specifically, using analyst reports from seven large global investment banks over 2000-2014, the study documents factors associated with the determinants of report length based on the supply (demand) of information by analysts (from investors). Among them, report length is more positively associated with a report with a recommendation upgrade, suggesting the credibility-enhancing explanation on a longer upgrade report.

The research also finds that report length is negatively correlated with forecast error, justifying that it is a valid proxy for analysts' research effort, which previous literature critically fails to show. Thus, it is expected that the positive association of longer reports with higher forecast accuracy is related to a stronger stock market reaction to both longer upgrade and downgrade reports.

However, the study documents an asymmetric market reaction to these upgrade and downgrade reports. Possibly due to analysts' conflicts of interest and/or motivation for access to management, reports with a favorable recommendation may be viewed as overly optimistic, and therefore less credible by investors, whereas report with an unfavorable one may be perceived to be more credible. By providing more useful details in the former, analysts justify their optimistically biased opinions in a form of longer reports. As a result, investors react more positively to longer reports with a favorable opinion, whereas they do not strongly react to the reports of the same length with an unfavorable rating. This suggests that besides forecast accuracy, the credibility is positively correlated with the informativeness in analyst reports.

Moreover, market reaction to longer upgrade reports is more (less) pronounced when they have more cash flow discussion (tables). This suggests that valuation-specific narrative is more useful than non-narrative valuation summary presented in a table for the credibility enhancement of upgrade reports. Market also displays stronger reaction to longer upgrades by a less experienced, busier, or male analyst, for a firm with greater information opacity or during bad time.

The research makes several significant contributions to the literature on analysts' research effort by finding various determinants of report length, showing its positive association with market reaction through accuracy, and thus confirming its validity as a proxy for analysts' research effort. Consequently, the study significantly extends prior research using page length as analysts' research effort (e.g., Feldman, Gilson, and Villalonga, 2010; Loh and Stulz, 2018).

More importantly, the paper shows a different motivation for longer reports between analysts and management, contributing to the literature on both *analyst* and *annual* report length as a proxy for readability or complexity. Thus, the study motivates researchers to examine the nature (or motivation) of other longer documents, contributing to the disclosure literature.

The study also contributes to analysts' optimism literature by showing that more information is better and increases the credibility of optimistically biased recommendations, resulting in a stronger market reaction to longer reports with a favorable rating.

Lastly, the findings have practical implication for general report users because counting pages is more practical than calculating the frequency for the users to measure analyst effort.

References

Bae, K., Stulz, R., and Tan, H., 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. *Journal of Financial Economics* 88, 581–606.

Barth, M. E., Kasznik, R., and McNichols, M. F., 2001. Analyst coverage and intangible assets. *Journal of Accounting Research* 39: 1-34.

Boni, L., and Womack, K. L., 2006. Analysts, Industries, and Price Momentum. *Journal of Financial & Quantitative Analysis* 41: 85–109.

Chen, X., Cheng, Q., and Lo, K., 2010. On the relationship between analyst reports and corporate disclosures: Exploring the roles of information discovery and interpretation. *Journal of Accounting and Economics* 49: 206–226.

Clement, M., 1999. Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter*?. Journal of Accounting and Economics* 27: 285–303.

Conrad, J., Cornell, B., Landsman, W., and Rountree, B., 2006. 'How Do Analyst Recommendations Respond to Major News?', *Journal of Financial and Quantitative Analysis,* 41; 25–49.

De Franco, G., Hope, O.K., Vyas, D., and Zhou, Y., 2015. Analyst report readability. *Contemporary Accounting Research* 32: 76–104.

Feldman, E.R., Gilson, S.C., and Villalonga, B., 2010. Do analysts add value when they most can? Evidence from corporate spin-offs. *Working paper*, Harvard Business School.

Francis, J., and Soffer, L., 1997. The relative informativeness of analysts' stock recommendations and earnings forecast revisions. *Journal of Accounting Research* 35: 193–211.

Gu, Z., and Wu, J., 2003. Earnings skewness and analyst forecast bias. *Journal of Accounting and Economics* 35; 5–29.

Hirst, E., Koonce, L., and Simko, P., 1995. Investor reactions to financial analysts' research reports. *Journal of Accounting Research* 33: 335–351.

Hong, H., and Kubik, J. D., 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance* 58: 313–51.

Huang, A., Zang, T., and Zheng, R., 2014. Evidence on the Information Content of Text in Analyst Reports. *The Accounting Review* 89: 2151–2180.

Hutton, A.P., Miller, G.S., and Skinner, D.J., 2003. The role of supplementary statements with management earnings forecasts. *Journal of Accounting Research* 41: 867-890.

Jacob, J., Lys, T. Z., and Neale, M. A.,1999. Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics*, 28: 51–82.

Jegadeesh, N., Kim, J., Krische, S., and Lee, C., 2004. Analyzing the Analysts: When Do Recommendations Add Value? *Journal of Finance* 59: 1083–1124.

Jegadeesh, N., and Kim, W., 2010. Do Analysts Herd? An Analysis of Recommendations and Market Reactions. *Review of Financial Studies* 23: 901–37.

Ke, B., and Yu, Y. 2006. "The Effect of Issuing Biased Earnings Forecasts on Analysts' Access to Management and Survival." *Journal of Accounting Research* 44: 965–99.

Klettke, T., Homburg, C., and Gell, S., 2015. How to Measure Analyst Forecast Effort. *European Accounting Review* 24: 129–146.

Kumar A., 2010. Self-selection and the forecasting abilities of female equity analysts. *Journal of Accounting Research* 48: 393-435.

Li, F., 2008. Annual Report Readability, Current Earnings, and Earnings Persistence. *Journal of Accounting and Economics* 45: 221–47.

Li, J., and Zhao, X., 2016. Complexity and Information Content of Financial Disclosures: Evidence from Evolution of Uncertainty Following 10-K Filings. *Working paper*. University of Texas at Dallas.

Ljungqvist, A., Marston, F., Starks L. T., Wei, K. D., and Yan, H., 2007. Conflicts of interest in sell-side research and the moderating role of institutional investors, *Journal of Financial Economics* 85: 420-56.

Loh, R., and Stulz, R., 2018. Is sell-side research more valuable in bad times?. *Journal of Finance* 73: 959-1013.

Loughran, T., and McDonald, B., 2014. Measuring Readability in Financial Disclosures. *Journal of Finance* 69: 1643–71.

Leuz, C., and Schrand, C., 2009. Disclosure and the cost of capital: Evidence from firms' responses to the Enron shock. *Working paper*, University of Chicago.

Michaely, R., and Womack, K., 1999. Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies* 12: 653–686.

Richardson, S., Teoh, S., and Wysocki, P., 2004. The Walk-down to Beatable Analyst Forecasts: The Role of Equity Issuance and Insider Trading Incentives. *Contemporary Accounting Research* 21: 885–924.

Rubin, A., Segal, B., and Segal, D., 2017. The interpretation of unanticipated news arrival and analysts' skill. *Journal of Financial and Quantitative Analysis* 52: 1491-1518.

Womack, K., 1996. Do Brokerage Analysts' Recommendations Have Investment Value? *Journal of Finance* 51: 137–67.

Zhang, F., 2006. Information uncertainty and analyst forecast behavior. *Contemporary Accounting Research* 23: 565–590.

Appendix A Variable Definitions

Variable	Definition
report length variable	
pagedec (*_dum*)	Deciles (a median dummy) of the number of pages (*page*) of analyst reports ranked by bank and year.
page	Number of pages of analyst reports. *page* is log-transformed in a regression (*logpage*).
recommendation variable	
upgrade	Equals to 1 if the analyst issues upward recommendation revision relative to prior recommendation for firm j at time t, and 0 otherwise.
downgrade	Equals to 1 if the analyst issues downward recommendation revision relative to prior recommendation for firm j at time t, and 0 otherwise.
buy	Equal to 1 for a strong buy or a buy recommendation, and 0 otherwise.
sell	Equals to 1 for a strong sell or a sell recommendation, and 0 otherwise.
determinant variable	
team	Equal to 1 if the report is issued by a team, i.e. at least 2 analysts, and 0 otherwise.
preearn (postearn)	Equal to 1 if the analyst report is made within 2 and 6 days before (after) a firm's earnings announcements, and 0 otherwise.
crisis	Global financial crisis equal to 1 if year is between 2007 and 2009, and 0 otherwise.
recession	Recession from March to November 2001 defined by National Bureau of Economic Research (NBER).
forecast accuracy variable	
afeprcm (*afeact*, *afeeps*) (%)	Analyst forecast error (in percentage) is measured as the absolute value of forecast error calculated as 100 times the difference between an analyst's last one-year ahead forecast at time t and a firm’s actual earnings (as reported in I/B/E/S) for year t divided by the latest available monthly stock price from Compustat before the forecast announcement date (the same actual earnings, the same forecast).
market reaction variable	
car5 (%)	Sum of daily market-adjusted abnormal return (in percentage) during one day before and 3 days after analysts' earnings forecast announcement (i.e., -1 to +3) with day 0 as analyst earnings forecast date); analyst forecast date from I/B/E/S.
detail variable	
table	Number of tables in the report at time t.
cf (%)	100*ratio of cash flow keywords to the number of total words in the report at time t; then multiplied by 100 for easy reading
interacting variable	
female	Equals to 1 if the analyst is a female, and 0 otherwise.
em	Earnings management measured as discretionary accruals by Modified Jones Model.
forecast frequency variable	
freq	Number of earnings forecasts the analyst makes for a firm in year t.
control variable	
brsize	Number of analysts employed at the brokerage firm (or investment bank) in year t.
firmexp	Firm experience, calculated as the number of years for which an analyst supplies a forecast for the firm in year t.
indexp	Industry experience, measured as the number of years since an analyst covered the firm’s industry in year t.
firmcover	Number of firms covered is defined as the number of firms an analyst follows in year t.
indcover	Number of industries covered is calculated as the number of industries an analyst follows in year t.
horizon	Number of days between a forecast date and an earnings announcement date in time t.

at	A firm's total assets in year t. at is log-transformed in a regression (*logat*).
mb	Ratio of market value to book value of a firm at the end of year t.
roa	Ratio of income before extraordinary items to total assets at the end of year t.
leverage	Total liabilities divided by total assets at the end of year t.
retstdpre1	Standard deviation of daily stock return for a firm during 1 year (i.e., 12 months) prior to an analyst forecast date.
loss	Indicator variable equal to 1 if a firm has a negative return on assets (*roa*), and 0 otherwise for year t.
nanalyst	Number of analysts following the firm in year t. *nanalyst* is log-transformed in a regression (*lognanalyst*).
afeactlag	*afeprcm* in time t-1.
displag	*disp* in time t-1. *disp* is analyst forecast dispersion, calculated as standard deviation of earnings forecasts for each firm and year divided by absolute value of its mean.
iholding	Institutional holding is measured as the total number of shares held by institutions divided by shares outstanding at the end of the same quarter in quarter t. The percentage holdings of institutional investors are 0 if no institutional investor reports positive holdings for a firm-quarter.
readability	Aggregate forecast readability measure of Fog, Flesch-Kincaid, Flesch Reading Ease, and Smog Readability Index by multiplying the first two and the last one by negative one to ensure that all components are increasing in readability, ranking each component into percentiles from 1 to 100, and then taking the average across the four components. The higher readability, the easier to read (its change value).

Table 1 Descriptive Statistics

This panel reports the summary statistics of the 351,629 analyst-firm-year observations during 2000-2014. All continuous variables are winsorized at 1 and 99 percentiles. See Appendix A for variable definitions.

Variable	N	Mean	Std Dev	Q1	Median	Q3
pagedec	351,629	5.460	2.789	3	5	8
page	351,629	8.538	4.858	5	7	10
upgrade	351,629	0.044	0.204	0	0	0
downgrade	351,629	0.046	0.209	0	0	0
buy	351,629	0.544	0.498	0	1	1
sell	351,629	0.069	0.254	0	0	0
car5 (%)	351,629	-1.710	6.152	-4.320	-1.421	1.108
afeprcm (%)	351,629	1.650	5.433	0.075	0.266	0.922
freq	351,629	10.439	6.591	6	9	11
table	351,629	7.049	8.462	1	4	10
cf (%)	351,629	0.027	0.056	0	0	0.035
preearn	351,629	0.006	0.078	0	0	0
postearn	351,629	0.008	0.090	0	0	0
female	351,533	0.381	0.486	0	0	1
team	351,629	0.890	0.313	1	1	1
em	336,051	0.059	0.079	0.015	0.035	0.069
crisis	351,629	0.177	0.381	0	0	0
recession	351,629	0.047	0.213	0	0	0
brsize	351,629	235.783	119.556	136	191	344
firmexp	351,629	3.496	3.303	0.904	2.496	5.196
indexp	351,629	4.684	3.431	1.937	3.932	6.770
firmcover	351,629	15.964	7.045	11	15	20
indcover	351,629	2.107	1.211	1	2	3
horizon	351,629	183.217	95.598	99	188	278
at	351,629	31658.180	97119.900	1540.460	5127.240	19924.000
mb	351,629	3.937	5.243	1.566	2.642	4.512
roa	351,629	0.084	0.114	0.041	0.085	0.140
leverage	351,629	0.573	0.234	0.414	0.575	0.735
retstdpre1	351,629	0.023	0.014	0.014	0.020	0.028
loss	351,629	0.167	0.373	0	0	0
nanalyst	351,629	15.077	7.783	9	14	20
afeprcmlag	351,629	1.613	5.193	0.076	0.269	0.930
displag	351,629	0.293	0.701	0.051	0.096	0.216
iholding	351,629	0.490	0.374	0	0.633	0.839
readability	351,629	53.909	26.492	32.667	54.667	76.333

Table 2 Sample Distribution By Year and Bank

Panel A: By Year

This table displays the sample distribution by year of the 351,629 analyst-firm-year observations in the sample period 2000-2014. The first three in *Overall* represent the total number of observations (nobs), firms (nfirm), and analysts (nanalyst), respectively, and the rest are an average value of *pagedec*, *page*, *upgrade*, *downgrade*, *afeprcm*, *table*, and *cf*, respectively. All continuous variables are winsorized at 1 and 99 percentiles. See Appendix A for variable definitions.

year	nobs	nfirm	nanalyst	pagedec	page	upgrade	downgrade	afeprcm	table	cf
2000	14,872	1,429	498	5.324	5.842	0.017	0.027	1.499	3.002	0.006
2001	22,520	1,567	543	5.358	5.214	0.030	0.038	2.089	2.845	0.007
2002	23,306	1,601	543	5.620	5.990	0.026	0.079	2.159	3.658	0.017
2003	23,474	1,485	525	5.562	8.561	0.044	0.049	1.241	5.733	0.023
2004	26,221	1,601	524	5.401	8.195	0.049	0.042	1.105	4.799	0.034
2005	28,738	1,654	531	5.512	8.697	0.052	0.045	1.292	5.597	0.030
2006	21,907	1,625	429	5.459	9.031	0.049	0.049	1.515	6.854	0.030
2007	20,032	1,483	396	5.446	9.211	0.059	0.049	2.096	8.297	0.028
2008	20,351	1,475	403	5.570	9.133	0.056	0.057	3.614	8.757	0.030
2009	21,755	1,478	375	5.360	8.947	0.051	0.049	2.696	8.684	0.031
2010	23,873	1,529	393	5.426	9.214	0.045	0.038	1.350	8.761	0.031
2011	25,493	1,542	399	5.493	9.731	0.044	0.039	1.330	9.776	0.030
2012	27,100	1,595	407	5.393	9.868	0.042	0.046	1.424	9.975	0.032
2013	24,931	1,646	373	5.445	10.031	0.040	0.044	1.116	9.803	0.035
2014	27,056	1,741	355	5.481	9.023	0.042	0.038	0.943	7.643	0.035
Overall	*351,629*	*23,451*	*6,694*	*5.457*	*8.446*	*0.043*	*0.046*	*1.698*	*6.946*	*0.027*

Panel B: By Bank

This panel shows the sample distribution by bank of the 351,629 analyst-firm-year observations in the sample period 2000-2014. The first three in *Overall* represent the total number of observations (nobs), firms (nfirm), and analysts (nanalyst), respectively, and , and the rest are an average value of *pagedec*, *page*, *upgrade*, *downgrade*, *afeprcm*, *table*, and *cf*, respectively. country is where the headquarter of a bank is located in. Variables with † are log-transformed in regressions due to high skewness. All continuous variables are winsorized at 1 and 99 percentiles. See Appendix A for variable definitions.

bank	nobs	nfirm	nanalyst	pagedec	page	upgrade	downgrade	afeprcm	table	cf	country
Citigroup	37,973	1,322	189	5.444	6.363	0.030	0.043	1.580	2.560	0.010	U.S.
Credit Suisse	80,059	2,223	404	5.536	7.529	0.042	0.044	1.863	5.821	0.035	Swiss

Deutsche Bank	45,176	1,776	304	5.510	10.068	0.034	0.038	1.601	8.810	0.045	Germany
Jeffries & Co.	13,092	819	101	5.274	5.996	0.037	0.047	1.706	2.255	0.055	U.S.
J.P. Morgan	47,486	1,536	204	5.474	8.380	0.028	0.029	1.251	4.539	0.036	U.S.
Morgan Stanley	57,646	1,712	353	5.528	10.687	0.032	0.043	1.441	8.852	0.015	U.S.A.
UBS	70,197	1,846	384	5.317	8.698	0.080	0.069	1.909	10.856	0.016	Swiss
Overall	*351,629*	*11,234*	*1,939*	*5.441*	*8.246*	*0.040*	*0.045*	*1.622*	*6.242*	*0.030*	

Table 3 Pearson Correlation Matrix

This table provides the Pearson correlation matrix among the main variables of the 351,629 analyst-firm-year observations in the sample period 2000-2014. All continuous variables are winsorized at 1 and 99 percentiles. See Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) pagedec											
(2) page	0.742***										
(3) upgrade	0.047***	0.054***									
(4) downgrade	0.023***	0.013***	-0.047***								
(5) afeprcm (%)	-0.037***	-0.042***	0.002	0.026***							
(6) table	0.576***	0.808***	0.070***	0.030***	-0.017***						
(7) cf (%)	0.089***	0.099***	0.003	-0.004***	-0.013***	0.069***					
(8) firmexp	-0.014***	0.067***	0.013***	0.004**	-0.049***	0.048***	0.030***				
(9) indcover	-0.000	0.004**	-0.009***	-0.006***	0.016***	-0.033***	0.027***	0.057***			
(10) female	-0.007***	-0.004**	-0.008***	-0.008***	-0.018***	-0.014***	-0.028***	0.058***	-0.018***		
(11) em	0.014***	-0.036***	-0.012***	0.001	0.119***	-0.030***	0.000	-0.147***	0.001	-0.033***	
(12) crisis	-0.001	0.053***	0.026***	0.013***	0.098***	0.084***	0.021***	0.001	-0.023***	0.003	0.009***

Table 4 Univariate Mean Comparisons

Panel A: By Deciles of Page

This panel shows the mean comparisons of main variables between the first (i.e., D1) and tenth (i.e., D10) decile (*pagedec*) of the number of pages of the 351,629 analyst-firm-year observations ranked by bank and year in the sample period 2000-2014. See Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	pagedec										*diff.*
Variable	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1-D10
upgrade	0.035	0.031	0.040	0.035	0.039	0.043	0.045	0.047	0.055	0.070	-0.035***
downgrade	0.040	0.037	0.042	0.040	0.050	0.047	0.049	0.052	0.050	0.052	-0.012***
afeprcm (%)	1.960	1.879	1.838	1.670	1.756	1.671	1.578	1.455	1.367	1.276	0.684***
table	2.109	2.373	2.864	3.829	4.953	5.785	7.179	9.254	12.226	21.962	-19.853***
cf (%)	0.021	0.022	0.022	0.027	0.023	0.029	0.028	0.033	0.034	0.037	-0.016***
firmexp	3.516	3.594	3.517	3.699	3.451	3.508	3.343	3.359	3.315	3.684	-0.168***
indcover	2.061	2.149	2.110	2.116	2.112	2.131	2.024	2.064	2.118	2.164	-0.103***
female	0.406	0.380	0.380	0.374	0.376	0.382	0.381	0.394	0.388	0.359	0.047***
em	0.056	0.058	0.056	0.057	0.062	0.060	0.062	0.061	0.061	0.057	-0.001
crisis	0.197	0.176	0.145	0.210	0.149	0.213	0.174	0.166	0.179	0.177	0.02***

Panel B: By Median of Page

This panel shows the mean comparisons of main variables between the median of the number of pages of the 351,629 analyst-firm-year observations ranked by bank and year in the sample period 2000-2014. An observation greater (smaller) than the median value (*pagedum*) is treated as high (low). See Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	low		high		low - high
Variable	N	Mean	N	Mean	*diff.*
upgrade	182,492	0.036	169,137	0.052	-0.016***
downgrade	182,492	0.042	169,137	0.050	-0.008***
afeprcm (%)	182,492	1.816	169,137	1.471	0.345***
table	182,492	3.300	169,137	11.094	-7.794***
cf (%)	182,492	0.023	169,137	0.032	-0.009***
firmexp	182,492	3.552	169,137	3.435	0.117***
indcover	182,492	2.114	169,137	2.099	0.015***
female	182,397	0.382	169,136	0.381	0.001

em	174,746	0.058	161,305	0.060	-0.002***
crisis	182,492	0.172	169,137	0.182	-0.010***

Table 5 Determinants of Report Length

This table shows multiple OLS regression results on the determinants of analysts' report length (*pagedec*) and its alternative measure (*logpage*). i (b, y, f, and a) stands for industry (bank, year, firm, and analyst). F-test is the coefficient equality test between *upgrade* and *downgrade*. See Table 6 for the specification and Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	pagedec	pagedec	logpage	logpage	pagedec	pagedec	logpage	logpage
Variables related to supply of information by analysts								
upgrade		**0.707*****		**0.114*****		**0.699*****		**0.111*****
		(13.05)		**(10.47)**		**(13.66)**		**(11.53)**
downgrade		**0.388*****		**0.058*****		**0.397*****		**0.059*****
		(6.15)		**(5.80)**		**(6.56)**		**(6.15)**
team	**0.241*****	**0.244*****	**0.074****	**0.074****	**0.296*****	**0.300*****	**0.082*****	**0.082*****
	(2.95)	(2.95)	(2.38)	(2.41)	(3.70)	(3.71)	(4.16)	(4.21)
preearn	0.134	0.126	0.024	0.023	0.057	0.050	0.014	0.013
	(0.84)	(0.80)	(0.86)	(0.82)	(0.38)	(0.34)	(0.57)	(0.53)
postearn	**0.833*****	**0.831*****	**0.152*****	**0.152*****	**0.779*****	**0.778*****	**0.136*****	**0.136*****
	(8.25)	**(8.26)**	**(6.08)**	**(6.04)**	**(8.04)**	**(8.11)**	**(6.70)**	**(6.68)**
retstdpre1	**-0.601***	**-0.630***	**-0.109****	**-0.114****	**-0.645*****	**-0.684*****	**-0.077****	**-0.083*****
	(-1.84)	**(-1.94)**	**(-2.00)**	**(-2.10)**	**(-3.33)**	**(-3.57)**	**(-2.93)**	**(-3.18)**
Variables related to demand of information from investors								
crisis	**0.348*****	**0.316*****	**0.622*****	**0.617*****	**-0.538**	**-0.566**	**0.658*****	**0.654*****
	(5.62)	**(5.18)**	**(18.44)**	**(18.09)**	**(-1.48)**	**(-1.57)**	**(9.90)**	**(9.83)**
recession	**0.315*****	**0.313*****	**0.025*****	**0.025*****	**0.251*****	**0.249*****	**0.014**	**0.014**
	(22.01)	**(21.97)**	**(3.66)**	**(3.64)**	**(6.69)**	**(6.64)**	**(1.25)**	**(1.22)**
Control variables								
brsize	1.323***	1.325***	-0.141	-0.141	1.068*	1.097*	0.168	0.172
	(3.13)	(3.14)	(-0.27)	(-0.27)	(1.89)	(1.95)	(0.66)	(0.69)
firmexp	-0.017**	-0.018**	-0.003**	-0.003**	0.007	0.006	0.000	0.000
	(-2.06)	(-2.15)	(-2.14)	(-2.22)	(1.48)	(1.32)	(0.24)	(0.13)
indexp	-0.017	-0.017	0.003	0.003	0.029	0.030	0.005	0.005
	(-1.07)	(-1.04)	(1.14)	(1.17)	(0.90)	(0.93)	(1.03)	(1.06)
firmcover	0.013	0.013	-0.001	-0.001	0.010	0.010	-0.003	-0.003
	(1.64)	(1.64)	(-0.68)	(-0.68)	(1.36)	(1.40)	(-1.21)	(-1.19)
indcover	-0.016	-0.015	0.005	0.005	0.048	0.049	0.008	0.008

	(-0.33)	(-0.32)	(0.69)	(0.69)	(1.17)	(1.19)	(0.99)	(1.00)
horizon	0.087	0.098	0.044	0.045	-0.017	-0.005	0.017	0.019
	(0.47)	(0.53)	(1.38)	(1.44)	(-0.11)	(-0.03)	(0.76)	(0.85)
logat	0.063***	0.062***	0.011***	0.010***	0.032	0.031	0.005	0.005
	(2.70)	(2.66)	(2.99)	(2.94)	(1.07)	(1.03)	(0.83)	(0.81)
mb	0.005	0.005	0.001	0.001*	0.001	0.001	0.000	0.000
	(1.51)	(1.63)	(1.62)	(1.75)	(0.45)	(0.55)	(1.01)	(1.08)
roa	0.394**	0.384**	0.044	0.043	0.056	0.063	-0.019	-0.018
	(2.15)	(2.08)	(1.37)	(1.31)	(0.30)	(0.33)	(-0.56)	(-0.53)
leverage	-0.189**	-0.193**	-0.019	-0.020	0.060	0.061	0.026**	0.026**
	(-2.01)	(-2.05)	(-1.23)	(-1.27)	(1.10)	(1.13)	(2.84)	(2.82)
loss	0.098*	0.097*	0.015	0.014	0.012	0.012	0.002	0.002
	(1.89)	(1.87)	(1.58)	(1.55)	(0.32)	(0.31)	(0.33)	(0.32)
lognanalyst	0.125***	0.125***	0.014*	0.014*	-0.053	-0.051	-0.009	-0.008
	(2.62)	(2.61)	(1.87)	(1.87)	(-0.97)	(-0.92)	(-1.26)	(-1.20)
iholding	-0.066*	-0.065*	-0.011*	-0.011*	0.036	0.036	0.008	0.008
	(-1.72)	(-1.71)	(-1.72)	(-1.71)	(1.33)	(1.33)	(1.64)	(1.67)
readability	0.014***	0.014***	0.002***	0.002***	0.019***	0.019***	0.003***	0.003***
	(5.48)	(5.48)	(5.63)	(5.63)	(5.18)	(5.40)	(5.83)	(5.35)
constant	2.693***	2.696***	1.043***	1.044***				
	(6.15)	(6.22)	(8.63)	(8.63)				
fixed effect	i/b/y	i/b/y	i/b/y	i/b/y	f/a/y	f/a/y	f/a/y	f/a/y
clustering	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y
F-test								
H_0: upgrade=downgrade		38.29***		61.70***		39.52***		75.28***
H_0: preearn=postearn		14.98***		10.68***		17.91***		13.10***
N	351,629	351,629	351,629	351,629	351,481	351,481	351,481	351,481
adj. R-sq	0.045	0.048	0.305	0.307	0.240	0.243	0.455	0.457

Table 6 Report Length and Earnings per Share (EPS) Forecast Error

This table reports multiple OLS regression results of page length on earnings per share (EPS) estimate error.

$$dependent = \beta_0 + \beta_1 pagedec + \beta_2 \Sigma analyst + \beta_3 \Sigma firm + \beta 4 industy\ F.E. + \beta_5 bank\ F.E. + \beta_6 year\ F.E. + \varepsilon$$

The dependent variables (*dependent*) are the proxies for either absolute forecast error (*afeprcm, afeact*, or *afeeps*) in year *t* in a forecast model. The key variable of interest (*pagedec*) is the proxy for analysts' research effort level measured as the deciles of the number of report pages ranked by bank and year. *logpage* is an alternative measure. In the market reaction model, *pagedec* (or *logpage*) is interacted with upgrade and downgrade, and the key variable of interest is *upgrade*pagedec* (or *logpage*). The rest of variables controls for factors which influence dependent variables from control variables of Table 5 and *retstdpre1*. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry, bank, and year dummies are not reported for brevity. Alternatively, this table also displays linear regression results with firm and analyst fixed effects of page length on earnings per share (EPS) estimate error. Coefficients on constants and year dummies are not reported. In a cross-sectional test using two subsamples, z-test is the coefficient equality test on *upgrade*pagedec* (or *logpage*) between two different regressions. The *t*-statistics in parentheses are based on standard errors adjusted for analyst-and year (or firm)-level clustering. See Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	afeprcm	afeact	afeeps	afeprcm	afeact	afeeps	afeprcm	afeact	afeeps	afeprcm	afeact	afeeps
pagedec	**-0.007*** **	**-0.001*** **	**-0.001*** **				**-0.006** **	**-0.001** **	**-0.000**			
	(-2.88)	**(-2.93)**	**(-2.91)**				**(-2.40)**	**(-2.36)**	**(-1.23)**			
logpage				**-0.035*** **	**-0.002**	**-0.004** **				**-0.023* **	**-0.001**	**-0.001**
				(-2.63)	**(-1.49)**	**(-2.44)**				**(-1.78)**	**(-0.74)**	**(-0.36)**
brsize	-0.132	-0.010	-0.015	-0.145	-0.010	-0.017	0.051	-0.008	-0.013	0.051	-0.008	-0.013
	(-1.27)	(-0.69)	(-0.73)	(-1.36)	(-0.79)	(-0.81)	(0.40)	(-0.40)	(-0.76)	(0.39)	(-0.40)	(-0.75)
firmexp	0.000	0.000	0.000	0.000	0.000	0.000	0.002	-0.000	0.000	0.002	-0.000	0.000
	(0.17)	(0.66)	(0.13)	(0.17)	(0.67)	(0.13)	(0.75)	(-0.01)	(0.01)	(0.72)	(-0.03)	(0.01)
indexp	-0.001	-0.001**	-0.001*	-0.001	-0.001**	-0.001*	-0.022*	-0.006***	-0.005***	-0.022*	-0.006***	-0.005***
	(-0.45)	(-2.42)	(-1.93)	(-0.36)	(-2.36)	(-1.86)	(-2.02)	(-4.84)	(-3.73)	(-2.03)	(-4.82)	(-3.73)
firmcover	-0.002*	0.000	-0.000	-0.002**	0.000	-0.000	-0.001	-0.000	-0.001	-0.001	-0.000	-0.001
	(-1.89)	(0.55)	(-0.26)	(-2.00)	(0.47)	(-0.33)	(-0.24)	(-1.07)	(-1.27)	(-0.28)	(-1.11)	(-1.28)
indcover	0.015**	0.001*	0.001	0.016**	0.002*	0.001	-0.006	-0.001	-0.001	-0.006	-0.001	-0.001
	(2.49)	(1.90)	(1.28)	(2.52)	(1.94)	(1.31)	(-0.38)	(-0.39)	(-0.57)	(-0.38)	(-0.40)	(-0.57)
horizon	2.289***	0.484***	0.482***	2.290***	0.484***	0.482***	2.712***	0.526***	0.526***	2.712***	0.526***	0.526***
	(10.02)	(9.92)	(9.65)	(10.01)	(9.91)	(9.64)	(9.97)	(9.80)	(9.86)	(9.96)	(9.80)	(9.86)
logat	0.011	-0.001	-0.002*	0.011	-0.001	-0.002*	0.122***	0.013***	0.007	0.122***	0.013***	0.007
	(1.14)	(-0.53)	(-1.72)	(1.14)	(-0.55)	(-1.72)	(4.35)	(3.42)	(1.62)	(4.35)	(3.42)	(1.62)
mb	-0.016***	-0.000	-0.001**	-0.016***	-0.000	-0.001**	-0.023***	-0.000	-0.000	-0.023***	-0.000	-0.000
	(-6.10)	(-1.06)	(-2.36)	(-6.11)	(-1.06)	(-2.36)	(-4.92)	(-0.20)	(-1.44)	(-4.88)	(-0.20)	(-1.44)
roa	-0.723***	-0.032**	-0.035**	-0.724***	-0.032**	-0.035**	-0.725***	-0.008	-0.045	-0.726***	-0.008	-0.045

	(-6.41)	(-2.04)	(-2.49)	(-6.43)	(-2.06)	(-2.50)	(-3.08)	(-0.27)	(-1.73)	(-3.09)	(-0.27)	(-1.73)
leverage	0.194***	0.024***	0.019***	0.194***	0.024***	0.019***	0.277***	0.019	0.007	0.277***	0.019	0.007
	(3.74)	(3.01)	(3.57)	(3.74)	(3.02)	(3.58)	(3.16)	(1.60)	(0.60)	(3.16)	(1.60)	(0.60)
retstdpre1	1.007***	0.060***	0.064***	1.007***	0.060***	0.064***	1.255***	0.028	0.037	1.257***	0.028	0.037
	(5.75)	(5.25)	(4.86)	(5.74)	(5.24)	(4.88)	(4.82)	(1.02)	(1.26)	(4.82)	(1.03)	(1.27)
loss	0.085	0.003	0.013*	0.084	0.003	0.013*	0.053	-0.013**	-0.010	0.053	-0.013**	-0.010
	(1.53)	(0.93)	(1.87)	(1.53)	(0.91)	(1.87)	(0.88)	(-2.48)	(-1.03)	(0.88)	(-2.48)	(-1.03)
lognanalyst	-0.027	-0.006**	-0.011***	-0.027	-0.006**	-0.011***	0.096**	-0.006	-0.009	0.096**	-0.006	-0.009
	(-1.47)	(-2.05)	(-4.11)	(-1.49)	(-2.07)	(-4.13)	(2.88)	(-1.07)	(-1.59)	(2.89)	(-1.07)	(-1.58)
iholding	-0.064***	0.009***	0.009***	-0.064***	0.009***	0.009***	-0.128***	0.001	-0.004	-0.128***	0.001	-0.004
	(-2.92)	(3.44)	(4.04)	(-2.92)	(3.45)	(4.04)	(-3.06)	(0.26)	(-0.87)	(-3.06)	(0.26)	(-0.88)
afeprcmlag	0.909***			0.909***			0.796***			0.796***		
	(49.57)			(49.57)			(37.17)			(37.18)		
afeactlag		0.831***			0.831***			0.787***			0.787***	
		(84.82)			(84.81)			(69.47)			(69.47)	
afeepslag			0.762***			0.762***			0.707***			0.707***
			(45.07)			(45.06)			(44.23)			(44.24)
displag	0.124**	0.036***	0.109***	0.124**	0.036***	0.109***	0.182***	0.034***	0.114***	0.183***	0.034***	0.114***
	(2.12)	(9.70)	(11.17)	(2.12)	(9.71)	(11.17)	(3.13)	(9.18)	(13.55)	(3.13)	(9.18)	(13.57)
constant	-0.499***	-0.061***	-0.042***	-0.482***	-0.061***	-0.040***						
	(-3.41)	(-4.01)	(-4.44)	(-3.23)	(-3.89)	(-4.29)						
fixed effect	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	f/a/y	f/a/y	f/a/y	f/a/y	f/a/y	f/a/y
clustering	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y
N	351,629	351,629	350,898	351,629	351,629	350,898	351,481	351,481	350,749	351,481	351,481	350,749
adj. R-sq	0.800	0.756	0.689	0.800	0.756	0.689	0.812	0.761	0.697	0.812	0.761	0.697

Table 7 Report Length and Market Reaction

Panel A: Report Length and Market Reaction to Recommendation Revision

This table reports OLS regression results of the impact of report length (*pagedec* and *logpage*) on the market reaction (*car5*) to recommendation changes. The regression specifications are the same as in Table 6, but exclude previous forecast error and dispersion. The key independent variables of interest are interaction terms (*upgrade***pagedec* (or *logpage*)). See Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	car5	car5	car5	car5	car5	car5	car5	car5
upgrade	0.233*	0.111	0.552***	0.624*	0.233*	0.111	0.552***	0.624**
	(1.78)	(0.30)	(4.30)	(1.80)	(1.66)	(0.39)	(4.23)	(2.36)
downgrade	-1.833***	-2.982***	-1.581***	-2.640***	-1.833***	-2.982***	-1.581***	-2.640***
	(-6.49)	(-5.70)	(-5.53)	(-5.07)	(-10.03)	(-9.56)	(-9.14)	(-8.68)
pagedec	0.002		0.014**		0.002		0.014***	
	(0.28)		(2.57)		(0.27)		(3.14)	
upgrade*pagedec	**0.111*** **		**0.086*** **		**0.111*** **		**0.086*** **	
	(5.83)		**(4.68)**		**(5.81)**		**(4.95)**	
*downgrade*pagedec*	-0.037		-0.043		-0.037		-0.043*	
	(-1.34)		(-1.59)		(-1.52)		(-1.87)	
logpage		0.050		0.114**		0.050		0.114***
		(1.17)		(2.67)		(1.53)		(4.16)
upgrade*logpage		**0.371** **		**0.211**		**0.371*** **		**0.211***
		(2.33)		**(1.46)**		**(3.05)**		**(1.88)**
*downgrade*logpage*		0.459**		0.398*		0.459***		0.398***
		(2.20)		(1.92)		(3.35)		(3.00)
brsize	0.090	0.109	-0.135	-0.136	0.090	0.109	-0.135	-0.136
	(0.29)	(0.36)	(-0.33)	(-0.32)	(0.33)	(0.40)	(-0.35)	(-0.35)
firmexp	-0.026**	-0.026**	-0.012	-0.012	-0.026***	-0.026***	-0.012*	-0.012*
	(-2.49)	(-2.47)	(-1.47)	(-1.51)	(-2.76)	(-2.72)	(-1.82)	(-1.79)
indexp	0.025***	0.025***	-0.045	-0.045	0.025***	0.025***	-0.045**	-0.045**
	(2.63)	(2.61)	(-1.49)	(-1.50)	(2.76)	(2.72)	(-2.42)	(-2.43)
firmcover	-0.011***	-0.010***	-0.004	-0.004	-0.011**	-0.010**	-0.004	-0.004
	(-3.34)	(-3.31)	(-0.68)	(-0.61)	(-2.31)	(-2.27)	(-0.67)	(-0.58)
indcover	0.025	0.024	-0.083*	-0.083*	0.025	0.024	-0.083**	-0.083**
	(1.20)	(1.18)	(-1.97)	(-1.97)	(0.77)	(0.76)	(-2.18)	(-2.17)

horizon	0.449*	0.446*	0.440*	0.438*	0.449***	0.446***	0.440***	0.438***
	(1.92)	(1.91)	(1.81)	(1.80)	(2.84)	(2.82)	(3.05)	(3.04)
logat	-0.361***	-0.361***	-0.314***	-0.314***	-0.361***	-0.361***	-0.314***	-0.314***
	(-9.95)	(-9.99)	(-4.16)	(-4.15)	(-6.98)	(-6.99)	(-3.60)	(-3.60)
mb	0.010	0.010	0.015**	0.014*	0.010	0.010	0.015***	0.014***
	(1.46)	(1.44)	(2.27)	(2.11)	(1.47)	(1.45)	(2.77)	(2.74)
roa	-1.216***	-1.219***	-1.964***	-1.962***	-1.216***	-1.219***	-1.964***	-1.962***
	(-3.29)	(-3.30)	(-4.01)	(-4.01)	(-2.70)	(-2.71)	(-4.66)	(-4.65)
leverage	-0.227	-0.227	0.276	0.273	-0.227	-0.227	0.276	0.273
	(-1.38)	(-1.38)	(1.59)	(1.58)	(-0.82)	(-0.82)	(1.21)	(1.20)
retstdpre1	-4.423***	-4.411***	-3.474***	-3.471***	-4.423***	-4.411***	-3.474***	-3.471***
	(-5.94)	(-5.90)	(-4.78)	(-4.76)	(-7.31)	(-7.29)	(-7.15)	(-7.14)
loss	-0.286***	-0.288***	-0.144*	-0.145*	-0.286**	-0.288**	-0.144	-0.145
	(-2.58)	(-2.59)	(-1.79)	(-1.81)	(-2.06)	(-2.07)	(-1.52)	(-1.53)
lognanalyst	-0.665***	-0.666***	-0.603***	-0.603***	-0.665***	-0.666***	-0.603***	-0.603***
	(-11.51)	(-11.51)	(-9.13)	(-9.13)	(-6.68)	(-6.69)	(-7.89)	(-7.89)
iholding	0.173*	0.174*	-0.160**	-0.160**	0.173	0.174	-0.160*	-0.160*
	(1.91)	(1.91)	(-2.37)	(-2.37)	(1.41)	(1.41)	(-1.75)	(-1.75)
readability	-0.003***	-0.003***	-0.006***	-0.006***	-0.003***	-0.003***	-0.006***	-0.006***
	(-4.03)	(-4.09)	(-6.24)	(-6.52)	(-3.80)	(-3.95)	(-8.91)	(-9.01)
constant	3.123***	3.091***			3.123***	3.091***		
	(5.94)	(5.73)			(3.38)	(3.34)		
fixed effect	i/b/y	i/b/y	f/a/y	f/a/y	i/b/y	i/b/y	f/a/y	f/a/y
clustering	a-y	a-y	a-y	a-y	f-a	f-a	f-a	f-a
N	351,629	351,629	351,481	351,481	351,629	351,629	351,481	351,481
adj. R-sq	0.037	0.037	0.143	0.143	0.037	0.037	0.143	0.143

Panel B: Statistical and Economic Effect of Report Length for Upgrade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	car5	car5	car5	car5	car5	car5	car5	car5
Statistical Significance								
*pagesdec+upgrade*pagedec*	0.113***	0.421***	0.1***	0.325*	0.113***	0.421***	0.1***	0.325*
Economic Significance								
Std. dev effect (*upgrade*pagedec* (or *logpage*)*std. dev))	15.295%	16.735%	11.871%	1.914%	15.295%	16.735%	11.871%	1.914%
Relative (Std. dev effect/abs(*car5*))	8.94%	9.79%	6.94%	5.55%	8.94%	9.79%	6.94%	5.55%

Table 8 Robustness Checks

Panel A: Buy and Sell Recommendation

Replicating the results of Column (1), (3), (5), and (7) of Table 7, these tables report OLS regression results of market reaction (*car5*) to *buy*/*sell* conditional on page length (*pagedec*). The regression specification is the same as in Table 6, but excludes previous forecast error and dispersion. Only the coefficients on key variables are reported for brevity. See Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)
	car5	car5	car5	car5
buy	0.461***	0.458***	0.461***	0.458***
	(5.62)	(5.89)	(6.57)	(8.37)
sell	-0.378***	-0.325***	-0.378***	-0.325***
	(-3.14)	(-3.36)	(-2.94)	(-3.27)
pagedec	-0.011	0.006	-0.011	0.006
	(-1.15)	(0.82)	(-1.31)	(0.92)
buy*pagedec	**0.022*** **	**0.018** **	**0.022** **	**0.018** **
	(2.65)	**(2.67)**	**(2.25)**	**(2.29)**
*sell*pagedec*	0.010	-0.005	0.010	-0.005
	(0.49)	(-0.30)	(0.55)	(-0.32)
controls	yes	yes	yes	yes
fixed effect	i/b/y	f/a/y	i/b/y	f/a/y
clustering	a-y	a-y	f-a	f-a
N	351,629	351,481	351,629	351,481
adj. R-sq	0.033	0.140	0.033	0.140

Panel B: Within-Bank Analysis

Replicating the results of Column (2) of Table 7, these tables report multiple OLS regression results of market reaction (*car5*) to *upgrade*/*downgrade* conditional on page length (*logpage*) for each bank. JPM (MS, CITI, CS, DBS, UBS, and JEF) is the abbreviation for J.P. Morgan (Morgan Stanley, Citigroup, Credit Suisse, Deutsche Bank, UBS, and Jeffries & Co). Only the coefficients on key variables are reported for brevity. See Table 6 for the regression specification and Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	JPM	MS	CITI	CS	DBS	UBS	JEF
	car5	car5	car5	car5	car5	car5	car5
upgrade	0.160	-1.247**	1.860	1.054	1.855***	-0.976***	-3.503*
	(0.21)	(-2.16)	(1.21)	(1.57)	(2.58)	(-4.71)	(-1.66)
downgrade	-3.071***	-3.655*	-3.801***	-2.815***	-4.001***	-1.020	-5.068***
	(-3.51)	(-1.91)	(-3.65)	(-3.87)	(-3.32)	(-1.05)	(-3.32)
logpage	0.003	0.045	0.247***	0.045	0.069	-0.055	-0.029
	(0.02)	(0.62)	(5.16)	(0.49)	(0.54)	(-0.50)	(-0.31)
upgrade*logpage	**0.668** **	**0.790*** **	**-0.248**	**-0.154**	**0.043**	**0.713*** **	**2.952*** **
	(2.18)	**(3.46)**	**(-0.34)**	**(-0.55)**	**(0.14)**	**(6.90)**	**(2.78)**
*downgrade*logpage*	0.109	0.664	0.801*	0.357	0.497	0.090	-0.080
	(0.30)	(0.93)	(1.88)	(1.14)	(0.90)	(0.21)	(-0.09)
controls	yes	yes	yes	yes	yes	yes	yes
fixed effect	i//y	i/y	i/y	i/y	i/y	i/y	i/y

clustering	a-y	a-y	a-y	a-y	a-y	a-y	a-y
N	47,486	57,646	37,973	80,059	45,176	70,197	13,092
adj. R-sq	0.042	0.045	0.039	0.036	0.043	0.034	0.056

Panel C: Additional Control Variables

Replicating the results of Column (1) and (3) of Table 7, these tables show multiple OLS regression results of market reaction (*car5*) to *upgrade*/*downgrade* conditional on page length (*pagedec*) after including *team* and *crisis* (*afeprcmlag* and *displag*) from the determinant (forecast error) regression. Only the coefficients on key variables are reported for brevity. See Table 6 for the regression specification and Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1) car5	(2) car5	(3) car5	(4) car5
upgrade	0.230*	0.242*	0.550***	0.555***
	(1.76)	(1.86)	(4.27)	(4.36)
downgrade	-1.832***	-1.803***	-1.580***	-1.564***
	(-6.49)	(-6.47)	(-5.53)	(-5.51)
pagedec	0.001	-0.001	0.014**	0.013**
	(0.20)	(-0.11)	(2.40)	(2.19)
upgrade*pagedec	**0.112*** **	**0.111*** **	**0.087*** **	**0.086*** **
	(5.87)	**(5.76)**	**(4.59)**	**(4.58)**
*downgrade*pagedec*	-0.036	-0.037	-0.043	-0.043
	(-1.33)	(-1.37)	(-1.57)	(-1.58)
team	0.024	0.026	0.021	0.019
	(0.52)	(0.54)	(0.42)	(0.39)
crisis	-0.563***	-0.383***	1.180***	1.276***
	(-8.16)	(-5.21)	(3.57)	(3.72)
recession	0.001	0.040***	0.054	0.080**
	(0.10)	(4.12)	(1.74)	(2.57)
preearn	0.607***	0.614***	0.580***	0.579***
	(4.33)	(4.45)	(4.07)	(4.08)
postearn	0.322*	0.311	0.230	0.222
	(1.70)	(1.64)	(1.34)	(1.28)
afeprcmlag		-0.048***		-0.041***
		(-6.64)		(-4.68)
displag		-0.200***		-0.142***
		(-4.27)		(-4.05)
controls	yes	yes	yes	yes
fixed effect	i/b/y	i/b/y	f/a/y	f/a/y
clustering	a-y	a-y	a-y	a-y
N	351,629	351,629	351,481	351,481
adj. R-sq	0.037	0.039	0.143	0.144

Table 9 Cross-Sectional Test on Market Reaction to Recommendation Revision

In this table, only the coefficients on key variables are reported for brevity. The regression specification is the same as in Table 6, but excludes previous forecast error and dispersion. The t-statistics in parentheses are based on standard errors adjusted for analyst-and year-level clustering. See Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

Panel A: Detailed Information

Replicating the results of Column (1) and (2) of Table 7, this table reports multiple OLS regression results of market reaction (*car5*) to *upgrade/downgrade* conditional on *pagedec* (or *logpage*) based on the median value of detail traits (*table* and *cf*) ranked by a brokerage firm and a forecast year. high (low) indicates when the value of detail traits is above (below) its median. The key variable of interest is *upgrade*pagedec (*or *logpage)*.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	table				cf			
	high	low	high	low	high	low	high	low
	car5	car5	car5	car5	car5	car5	car5	car5
upgrade	0.510	0.160	0.871	-0.181	0.028	0.431**	-0.008	0.241
	(1.28)	(1.59)	(1.26)	(-0.46)	(0.14)	(2.06)	(-0.02)	(0.63)
downgrade	-1.913***	-1.583***	-2.960***	-3.147***	-1.563***	-2.068***	-2.384***	-3.631***
	(-3.99)	(-6.05)	(-6.66)	(-4.11)	(-4.57)	(-6.38)	(-4.17)	(-6.63)
pagedec	0.006	0.004			-0.009	0.012		
	(0.47)	(0.41)			(-0.94)	(1.61)		
upgrade*pagedec	**0.078***	**0.120*****			**0.150*****	**0.072****		
	(1.65)	**(5.04)**			**(5.83)**	**(2.08)**		
*downgrade*pagedec*	-0.010	-0.125***			-0.057	-0.021		
	(-0.19)	(-3.77)			(-1.44)	(-0.53)		
logpage			0.119*	0.012			-0.007	0.100*
			(1.92)	(0.21)			(-0.10)	(1.96)
upgrade*logpage			**0.095**	**0.449****			**0.448****	**0.288**
			(0.35)	**(2.22)**			**(2.11)**	**(1.62)**
*downgrade*logpage*			0.437***	0.572			0.234	0.710***
			(2.62)	(1.59)			(0.99)	(3.23)
controls	yes	yes	yes	yes	yes	yes	yes	yes
fixed effect	i/b/y	i/b/y	i/y/b	i/y/b	i/b/y	i/b/y	i/y/b	i/y/b
clustering	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y
Z-test	-0.784		-1.931*		1.820*		0.574	
N	175,849	175,780	175,849	175,780	175,849	175,780	175,849	175,780

adj. R-sq	0.036	0.038	0.036	0.038	0.034	0.040	0.034	0.040

Panel B: Analyst Characteristics

Replicating the results of Column (1) and (2) of Table 7, this table reports multiple OLS regression results of market reaction (*car5*) to upgrade/downgrade conditional on *pagedec* (or *logpage*) based on the median value of detail traits (*table* and *cf*) ranked by a brokerage firm and a forecast year. high (low) indicates when the value of detail traits is above (below) its median. yes (no) indicates when the report is issued by a female (male). The key variable of interest is *upgrade*pagedec* (or *logpage*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	firmexp				indcover				female			
	high	low	high	low	high	low	high	low	yes	no	yes	no
	car5	car5	car5	car5	car5	car5	car5	car5	car5	car5	car5	car5
upgrade	0.295*	0.161	0.607	-0.458	0.000	0.497**	-0.296	0.538	0.369***	0.147	0.367	-0.034
	(1.76)	(0.69)	(1.43)	(-0.93)	(0.00)	(2.49)	(-0.62)	(1.48)	(2.76)	(0.78)	(0.88)	(-0.08)
downgrade	-1.432***	-2.284***	-2.751***	-3.432***	-1.573***	-2.088***	-2.726***	-3.307***	-1.714***	-1.906***	-2.437***	-3.288***
	(-4.54)	(-7.56)	(-4.28)	(-6.80)	(-5.47)	(-5.83)	(-5.02)	(-5.33)	(-5.53)	(-6.02)	(-4.43)	(-5.72)
pagedec	0.002	0.002			0.002	0.002			0.014	-0.005		
	(0.29)	(0.21)			(0.25)	(0.27)			(1.58)	(-0.73)		
upgrade*pagedec	**0.077*** **	**0.149*** **			**0.152*** **	**0.068** **			**0.072*** **	**0.135*** **		
	(4.05)	**(4.60)**			**(8.42)**	**(1.98)**			**(2.99)**	**(5.02)**		
*downgrade*pagedec*	-0.050*	-0.015			-0.033	-0.039			-0.020	-0.045		
	(-1.70)	(-0.36)			(-1.15)	(-1.06)			(-0.51)	(-1.42)		
logpage			0.008	0.081			0.034	0.063			0.113*	0.027
			(0.22)	(1.22)			(0.59)	(1.09)			(1.81)	(0.63)
upgrade*logpage			**0.073**	**0.703*** **			**0.572*** **	**0.170**			**0.203**	**0.468*** **
			(0.41)	**(3.34)**			**(3.01)**	**(0.98)**			**(1.04)**	**(2.70)**
*downgrade*logpage*			0.518*	0.507**			0.477**	0.479*			0.294	0.551**
			(1.95)	(2.42)			(2.26)	(1.88)			(1.32)	(2.32)
controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
fixed effect	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y
clustering	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y
Z-test	-1.899*		-2.288**		2.193*		1.557		-1.753*		-1.016	
N	175,849	175,780	175,849	175,780	175,849	175,780	175,849	175,780	134,081	217,452	134,081	217,452
adj. R-sq	0.044	0.032	0.044	0.032	0.039	0.037	0.038	0.037	0.041	0.035	0.041	0.035

Panel C: Information Asymmetry and Uncertainty across Firms

Replicating the results of Column (1) and (2) of Table 7, this table shows multiple OLS regression results of market reaction (*car5*) to *upgrade*/*downgrade* conditional on *pagedec* (or *logpage*) based on the median value of information environment characteristics (*em* and *crisis*) ranked by a brokerage firm and a forecast year. high (low) indicates when the value of information asymmetry (*em*) is above (below) its median. yes (no) indicates when information uncertainty (*crisis*) (does not) exit(s). The key variable of interest is *upgrade*pagedec (*or *logpage).* In this table, only the coefficients on key variables are reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for analyst-and year-level clustering. See Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	em				crisis			
	high	low	high	low	yes	no	yes	no
	car5	car5	car5	car5	car5	car5	car5	car5
upgrade	0.060	0.430***	-0.143	0.391	-0.116	0.325**	-1.776***	0.395
	(0.37)	(2.67)	(-0.34)	(1.02)	(-0.53)	(2.38)	(-4.53)	(1.03)
downgrade	-2.012***	-1.691***	-2.842***	-3.048***	-1.169***	-1.993***	0.432	-3.337***
	(-5.56)	(-6.20)	(-4.75)	(-4.46)	(-13.13)	(-6.10)	(0.46)	(-7.16)
pagedec	-0.011	0.012***			-0.012	0.003		
	(-1.11)	(2.65)			(-1.14)	(0.58)		
upgrade*pagedec	**0.148*****	**0.079*****			**0.181*****	**0.093*****		
	(7.51)	**(3.18)**			**(3.42)**	**(5.99)**		
*downgrade*pagedec*	-0.029	-0.042			-0.086***	-0.025		
	(-0.66)	(-1.39)			(-2.70)	(-0.80)		
logpage			-0.013	0.084*			-0.047	0.070
			(-0.17)	(1.80)			(-0.82)	(1.54)
upgrade*logpage			**0.519*****	**0.239**			**1.251*****	**0.230**
			(3.00)	**(1.38)**			**(5.30)**	**(1.44)**
*downgrade*logpage*			0.325	0.545*			-0.969**	0.595***
			(1.33)	(1.95)			(-2.35)	(3.23)
controls	yes	yes	yes	yes	yes	yes	yes	yes
fixed effect	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y	i/b/y
clustering	a-y	a-y	a-y	a-y	a-y	a-y	a-y	a-y
Z-test	2.182**		1.144		1.606		3.589***	
N	168,090	167,961	168,090	167,961	62,138	289,491	62,138	289,491
adj. R-sq	0.035	0.043	0.035	0.044	0.046	0.035	0.046	0.035

Table 10 Report Length and Forecast Frequency

This table reports multiple OLS regression results of page length on forecast frequency. For a consistent unit of analysis with *freq*, both *pagedec* (or *logpage*) and control variables (*horizon* and *iholding*) are the averages within firm-analyst-year, i.e., *pagedecmn, logpagemn, horizonmn,* and *iholdingmn.* The key variable of interest is *pagedecmn* (or *logpagemn*). All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry, year, and bank dummies are not reported for brevity. The t-statistics in parentheses are based on standard errors adjusted for analyst-and year-level clustering. See Table 6 for the regression specification and Appendix A for variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)
	freq	freq	freq	freq
pagedecmn	**-0.124***		**-0.265*****	
	(-1.88)		**(-4.45)**	
logpagemn		**-1.053****		**-1.979*****
		(-2.46)		**(-5.80)**
brsize	0.805	0.591	1.874	2.087
	(0.23)	(0.18)	(0.85)	(1.05)
firmexp	0.062**	0.057**	0.111***	0.104***
	(2.53)	(2.34)	(4.29)	(4.14)
indexp	-0.011	-0.004	0.066	0.074
	(-0.37)	(-0.12)	(1.43)	(1.56)
firmcover	-0.002	-0.005	0.042	0.032
	(-0.10)	(-0.28)	(1.31)	(1.09)
indcover	0.367**	0.377**	0.189	0.194
	(2.46)	(2.53)	(1.61)	(1.69)
horizonmn	5.198***	5.220***	5.994***	5.974***
	(5.11)	(5.05)	(7.94)	(7.73)
logat	1.243***	1.253***	0.918***	0.923***
	(17.85)	(17.61)	(7.49)	(7.49)
mb	0.088***	0.088***	0.047***	0.048***
	(7.98)	(7.95)	(4.48)	(4.43)
roa	4.886***	4.913***	2.362***	2.347***
	(4.83)	(4.81)	(4.92)	(4.78)
leverage	-1.704***	-1.697***	-0.684**	-0.620*
	(-5.10)	(-5.09)	(-2.24)	(-2.09)
retstdpre1	3.185***	3.143***	0.993	1.008
	(3.64)	(3.56)	(1.59)	(1.65)
loss	0.665***	0.671***	0.148	0.160
	(3.73)	(3.78)	(1.22)	(1.31)
lognanalyst	0.483***	0.479***	0.300**	0.290**
	(3.93)	(3.90)	(2.33)	(2.29)
iholdingmn	0.715***	0.700***	0.880***	0.841***
	(3.90)	(3.76)	(4.65)	(4.43)
constant	-1.308	-0.319		
	(-0.79)	(-0.20)		
fixed effect	i/b/y	i/b/y	f/a/y	f/a/y
clustering	a-y	a-y	a-y	a-y
N	351,629	351,629	351,481	351,481
adj. R-sq	0.237	0.239	0.552	0.555

Impact of Environmental Disclosure in 10-K filings on Future Stock Price Crash Risk: Textual Analysis

Abstract

Using textual analysis, the study examines the determinants of environmental disclosure (ED) in U.S. 10-Ks and its impact on the future stock price crash risk. The level of (change in) ED is positively (negatively) associated (autocorrelated) with litigation risk (one-year pre/post change). Moreover, 10-Ks contain more negative ED than positive one. Accordingly, the research finds the negative association of ED with short term returns, showing that ED is bad news for managers to hide. In the long term, increased ED results in decreased risk in significant stock price drop. Change and instrument variable analyses mitigate endogeneity and identify a potential causation. The results are consistent with the notion that firms benefit from non-financial information disclosure.

Keywords: Environmental disclosure; Stock price crash risk; Managers' bad news hoarding tendency; 10-Ks; Textual analysis

1. Introduction

SEC Regulation S-K and accounting standards relating to contingencies (SFAS No. 5) mandate a firm to disclose a probable and reasonably estimated environmental expenditure in financial statements in 10-Ks. Due to the limitations of accounting rules, however, a firm may discretionarily disclose supplementary environmental information in 10-Ks. The study expands the literature on the value relevance of environmental disclosure by examining the impact of environmental disclosure in 10-Ks on future stock price crash risk based on managers' bad news hoarding tendency.

Due to information asymmetry and agency problem, opportunistic management tends to hoard bad news than good news until a tipping point when a large amount of bad news is abruptly released, leading to a sudden drop in stock price or a crash (Jin and Myers, 2006). Accordingly, disclosing the negative nature of environmental information mitigates managers' bad news hoarding incentive, resulting in less crash risk.

Based on textual analysis of 81,826 10-Ks filed to Securities and Exchange Commission (SEC) by U.S. firms during 1998-2013, the research first identities disclosed environmental information as bad news by documenting its positive relationship of environmental disclosure with litigation risk which is another bad news. The study also finds evidence of disclosed environmental information as bad news by showing that environmental disclosure is mean reverting since bad news is more likely to be concealed relative to good news. Additionally, the research provides direct evidence by finding that negative environmental information is disclosed more than positive environmental information by 1.2%. Meanwhile, if this is the case, the stock market should negatively react to environmental disclosure around a 10-K filing date. The research confirms this by documenting a significantly negative association of environmental disclosure with cumulative abnormal returns two days before and after the filing date. Thus, the study shows that disclosed environmental information in 10-Ks is bad news, thereby allowing for the examination of whether environmental disclosure reduces future crash risk based on the hypothesis that managers tend to hoard bad news.

The paper provides empirical evidence that a firm with more environmental disclosure is less likely to experience major price drops in the future because of a lower tendency on the part of managers to hoard bad news. The logit regression shows that a one standard deviation increase of environmental disclosure reduces the odds of future crash risk by 10%, holding everything else constant. On the other hand, the findings are robust to different measures of environmental disclosure such as its change, dummy, and residual. Using two exogenous shocks as an instrumental variable, the research further identifies a potential causality, over and above mitigating potential endogeneity issues. Overall, the results are consistent with the idea that firms benefit from non-financial information disclosure (e.g., Amir and Lev, 1996).

The research also examines the determinants of environmental disclosure, and finds its positive (negative) association with current return, firm size, leverage, litigation risk, the membership of environment-sensitive industry, and 10-K file size (previous return volatility, and turnover). More importantly, Neu, Warsame, and Pedwell (1998) find the complementary role of other social disclosures to environmental disclosure in 10-Ks because they help to frame the interpretation of environmental disclosure. Motivated by this, the paper documents that disclosed environmental information is positively (negatively) associated with human rights (product responsibilities).

The study makes the following important contributions. First, the paper adds to a growing literature on non-financial disclosure and its economic consequences by showing that environmental disclosure predicts future crash risk. Prior studies on environmental disclosure focus on its impact on return performance. However, the study establishes a potential causal relationship between environmental disclosure and ex-post crash risk using two exogenous shocks as an instrumental variable.

The study also contributes to the literature on stock price crash risk by comparing two different proxies for crash risk, i.e., one from finance and another from accounting literature. Previous crash risk studies (e.g., Hutton, Marcus, and Tehranian, 2009) measure crash risk based on firm-specific weekly abnormal returns that is net of market and industry influences. Contrary to this prior research, following Savor (2012), the paper introduces another crash risk measure considering the effect of a market, size, and value factor. This addition broadens the understanding of the impact of environmental disclosure on firms and stakeholders.

The research contributes to the literature using textual analysis by showing its usefulness to identify an underlying theory of managers' bad news hoarding. On the other hand, to my knowledge, the sample of 81,826 firm-year observations from mandatory 10-K filings during 1998 to 2013 is by far the largest among textual analysis on either environmental disclosure or crash risk. A large sample size allows the study to examine and generalize the economic consequences of environmental disclosure and especially, its causality using exogenous shocks. Previous textual analyses on environmental disclosure or crash risk have less sample size. For example, Ertugrul, Lei, Qiu, and Wan (2017) with 32,207 10-Ks for annual report readability-crash risk test, Cho and Patten (2007) with 100 10-Ks for environmental disclosure-environmental performance test during 2002, Neu, Warsame and Pedwell (1998) with 330 10-Ks from 33 Canadian firms for environmental disclosure-external pressure test, and Patten (1992) with 131 10-Ks for environmental disclosure-Alaskan oil spill test.

This paper proceeds as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 explains the research design and the sample collection. Section 4 presents the main empirical analysis. Section 5 describes the robustness checks. Section 6 discusses the identify strategies. Section 7 concludes the paper.

2. Literature review and Hypothesis development

In this section, the study reviews literature on the consequences of mandatory and/or voluntary environmental disclosure since its main investigation is on the stock price crash risk impact of environmental disclosure explained by managers' had news hoarding tendency. Based on the explanation, two hypotheses are developed.

2.1 Literature on consequences of environment disclosure

Under SEC regulations (e.g., Regulation S-K) as well as accounting standards on contingencies (SFAS No. 5), a firm must disclose a probable and reasonably estimated environmental expenditure in financial statements in 10-Ks.[17] The rules on environmental disclosures in 10-Ks include items 101/103/104/303 from Securities Act of 1933 and Securities Exchange Act of 1934 and Staff Accounting Bulletin No. 92. Appendix 1 briefly discusses these SEC rules on environment disclosure.

Different from mandatory environmental disclosure, voluntary environmental disclosure is not required by the SEC. Grossman (1981) and Milgrom (1981) argue that a firm should voluntarily disclose all relevant information to prevent an unjustified undervaluation due to information asymmetry. In contrast, there is a lack of full voluntary environmental disclosure based on legitimacy theory (e.g., Gray, Kouhy and Lavers, 1995b; Deegan, 2002: Patten, 1992;

[17] With regard to the measurement of a contingent loss, FASB Interpretation No. 14, Reasonable Estimation of the Amount of a Loss, states that the minimum be accrued when the reasonable estimate of a loss is a range but no amount within the range is a better estimate than any other amount.

Neu, Warsame and Pedwell, 1998), information asymmetry from agency theory (e.g., Li, Richardson and Thornton, 1997), and economics-based theory (e.g., Li, Richardson and Thornton, 1997). In sum, the level of voluntary environmental disclosure changes depending on the environmental information demand from stakeholders or on the motivations on the environmental information supply from managers.

Previous studies on the economic impact of environmental disclosure fall largely into three streams depending on its types (i.e., mandatory or voluntary) and consequences. The first stream examines the value relevance of disclosed environmental information under SEC-mandated environmental disclosure requirements (Blacconiere and Patten, 1994; Blacconiere and Northcut, 1997; Al-Tuwaijri, Christensen, and Hughes, 2004). The consensus is that more mandatory environmental disclosure is positively related to firm value, suggesting that mandatory disclosure reduce information asymmetry between managers and investors (Lev, 1988). In other words, investors interpret environmental disclosure as a positive sign for firms to manage their exposures to future regulatory costs, which thus positively influences a firm's value.

Compared to the studies on the effect of the mandatory environmental disclosure, the second stream of literature examines stock market reactions to voluntary environmental disclosure. The findings remain inconclusive due to the heterogeneous nature of the information discretionarily disclosed. For instance, Belkaoui (1976) shows positive abnormal stock returns for voluntary announcements of expenditure on pollution control in the annual report. However, Ingram (1978) reports no stock performance impact of voluntary social responsibility disclosures regarding the environment, fair business, personnel, community, and product in the annual reports of Fortune 500 companies.

The third steam examines the impact of environmental disclosure on the cost of capital. Richardson and Welker (2001) find that voluntary social disclosure including environmental disclosure in Canadian annual reports increases the cost of equity capital, especially for more profitable firms.[18] Their findings are opposite to the notion that discretionary disclosure reduces information asymmetry.

Thus, another economic impact of environmental disclosure, i.e., stock price crash risk, has not been explored for a long period of time.

2.2 Hypothesis development: environmental disclosure and crash risk

The study expands the literature on the value relevance of environmental disclosure by exploring the effect of environmental disclosure in 10-Ks on stock price crash risk. The underlying theory to explain its impact on crash risk is managers' bad news hoarding tendency.

Pae (2005) argues that a firm with information advantage tends to hoard bad news than good news, resulting in an increase in investor uncertainty. Considering this, Jin and Myers (2006) conjecture that when management cannot hoard bad news up to some tipping point, a large amount of bad news is abruptly and immediately released to the stock market, leading to a sudden drop in stock price, i.e., a crash. They contend that the probability and magnitude of a future stock price crash risk increases with the opacity of financial reporting which incentivizes a manager to withhold bad news from public disclosure.

The economics-based theory also supports the manager's bad news hoarding tendency which depends on the cost-benefit outcome of disclosure (Chambers and Penman, 1984; Kross and Schroeder, 1984), and career concerns and management compensation structure (Nagar, 1999; Nagar, Nanda, and Wysocki, 2003; Kothari, Shu, and Wysocki, 2009). However, litigation

[18] One explanation for this is that a firm discloses more social information to promote itself. That is, it overreports its positive contributions, but underreports negative social effects.

risk and reputation concerns motivate managers to quickly reveal bad news (Kasznik and Lev, 1995; Skinner, 1994, 1997). Accordingly, future stock price crash risk has a positive association with discretionary accruals (Hutton, Marcus and Tehranian, 2009), complex tax planning (Kim, Li, and Zhang, 2011a, 2011b), and an executive compensation package (Benmelech, Kandel, and Veronesi. 2010; Kim, Li, and Zhang, 2011b), but a negative relationship with the adoption of International Financial Reporting Standards (DeFond, Hung, Li, and Li, 2015), accounting conservatism (Kim and Zhang, 2015), and earnings smoothing (Chen, Kim, and Yao, 2015).

Using a CSR performance score from the MSCI ESG database, Kim, Li, and Li (2014) find that a firm with a better score has a lower crash risk. Following them, previous research has mixed results. Lu and Nakajima (2014) show that CSR has no effect on reducing the stock price crash risk of Japanese firms. Contrary, Lee and Lee (2016) show that CSR significantly mitigates Taiwanese stock price crash risk. Similarly, Zhang, Xie, and Xu (2016) document the negative impact of corporate philanthropic action on crash risk in China.

Methodologically, Kim, Li, and Li (2014) use a CSR performance index from the MSCI ESG database which scores the existence of disclosure items from firms' annual reports and CSR reports. However, the study focuses on the annual report filed by publicly traded firms pursuant to the Securities Exchange Act of 1934 in Form 10-K which is the primary source of information for capital market participants such as shareholders, creditors, and financial analysts.

To investigate the effect of environmental disclosure on future crash risk, it is critical to show that environmental disclosure is bad news that management tends to keep inside the firm for an extended period. Using SEC-registered mine owners, Christensen, Floyd, Liu, and Maffett (2017) document a negative short-window market reaction around the disclosure of immediate danger orders (IDOs) through a Form 8K filing required by 2010 Dodd-Frank Act, suggesting that IDOs are bad news which investors react negatively. They argue that the inclusion of information on social responsibility (i.e., safety at work) in financial reports can have a real effect.

As a major component of CSR, it is worth to investigate the economic consequence of environmental disclosure in 10-Ks. Thus, the study hypothesizes that more environmental information in 10-Ks reduces information asymmetry for external investors, which mitigates a manager's bad news hoarding incentive, leading to less crash risk than a firm with less voluntary environmental disclosure. In sum, the research predicts that firms with more environmental disclosure in 10-Ks are less likely to experience major price drops in the future due to less bad news hoarding from management.

Hypothesis 1: Environmental information disclosed in 10-K filings is negatively related with short-term market reaction.

Hypothesis 2: Environmental information disclosed in 10-K filings is negatively related with future stock price crash risk.

3. Research methodology and sample

3.1 Measurement of environmental disclosure in 10-K filings

Studies on environmental disclosure focus on the quantity (e.g., Neu, Warsame and Pedwell, 1998; Patten, 1992), the thematic content (e.g., Hughes, Anderson, and Golden, 2001), and the tone (Cho, Roberts, and Patten, 2010). This reflects the intense debate on the most appropriate unit of analysis for textual analysis (Gray, Kouhy and Lavers, 1995b). Nevertheless, most studies on social and environmental disclosure tend to use one or a combination of words, sentences, and pages (Hackston and Milne, 1996). Following this, the study uses a dictionary (i.e., a collection of keywords) approach to extract every environment-related sentence. The research creates a dictionary that is tailored to environmental disclosure in 10-K filings based on the following procedures.

1) I download 10-Ks from SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database. I randomly select twenty-two 10-Ks and read each of them to manually extract a word and phrase that is related to environmental information.
2) Since environmental activity is an integral part of CSR dimensions, I also search the keywords in the CSR-related websites such as Global Reporting Initiative (GRI) and MSCI ESG indexes.
3) I combine all the keywords from Step 1 and 2 to generate the preliminary dictionary of environmental disclosure. Using a Java program, I identify every sentence from a 10-K filing that contains any of the keywords in the dictionary.
4) I manually verify each and every keyword by reading more than twenty randomly-selected sentences that include the keyword.

Appendix 2 reports the top fifty most frequent environment-related keywords in 10-Ks. Appendix 3 shows examples of sentences on environmental disclosure. To measure the overall level of environmental disclosure in 10-Ks, I count the total number of environment-related keywords in each 10-K filing.

For a change analysis, I compute the change in the total number of environment-related keywords from year *t-1* to year *t*, scaled by the average number of environment-related keywords in the 10-K filings for the years, i.e., $\Delta env_t=(\Delta env_t-\Delta env_{t-1})/(\Delta env_t+\Delta env_{t-1})$.

For more robustness checks, I also create two alternative measures of environmental disclosure: 1) a dummy variable of environmental disclosure equal to one if the number of environment-related keywords in a 10-K filing is above its median, and zero otherwise in year *t*, and 2) a continuous variable of abnormal environmental disclosure equal to residuals from regressing environmental disclosure on explanatory variables in year *t*. See Appendix 4 for variable definitions.

3.2 **Measurement of short-term market reaction**

To test the short-term market reaction to environmental disclosure, the dependent variable, cumulative abnormal return (*car5*), is measured as the sum of daily market-adjusted abnormal return during five ([-2, +2]) days starting from two days before a 10-K filing date as day 0.

$$car5_{i,t} = exp[\sum_{t=-2}^{2} ln(1 + returni,t - vwretdi,t)] - 1 \qquad (1)$$

where $return_{i,t}$ is the daily stock return, and $vwretd_{i,t}$ is the value-weighted market return on stock i in time t. Specifically, 10-K filing dates are captured from a 10-K per se downloaded from SEC's EDGAR database. The daily stock return is based on the holding period return from CRSP, and the market return is the daily value-weighted return including all distributions of U.S. stocks from CRSP. Appendix 4 provides variable definitions.

3.3 Measurement of crash risk

The study uses two different proxies for crash risk depending on reflecting significant changes in fundamentals or investor sentiment. The first and main crash risk measure (*shockff3*) follows the spirit of Savor (2012). Savor (2012) defines major price movements as any firm-date observation where the absolute value of the Fama-French three-factor plus momentum model-adjusted abnormal return exceeds 10%.[19] He argues that 10% threshold is “high enough to screen out most price movements that do not reflect either substantial changes in fundamentals (or

[19] Savor (2012) finds that the results hold even if returns are scaled by their lagged volatility.

market perception thereof) or in investor sentiment”. Atkins and Dyl (1990) and Bremer and Sweeney (1991) also use the 10% thresholds to define large price declines.

Following them, firm-specific weekly abnormal return is measured as the residual return from the Fama-French three-factor model below that is net of market, firm size and firm value influences.

$$R_{i,t}-R_{f,}=\alpha_i+\beta_{i,m}(R_{m,t}-R_{f,t})+\beta_{i,smb}SMB_t+\beta_{i,hml}HML_t+\varepsilon_{i,i}, \tag{2}$$

where $R_{i,}$ is the firm’s return, $R_{m,}$ is the market return (i.e., CRSP value-weighted), $R_{f,t}$ is the risk-free rate, SMB_t is the return difference between a portfolio of small and big stocks (size factor), and HML_t is the return difference between a portfolio of high and low book-to-market stocks in week t (value factor). Then, following Savor (2012), Atkins and Dyl (1990), and Bremer and Sweeney (1991), a major price drop, *shockff3*, is an indicator equal to one if weekly firm-specific abnormal return ($\varepsilon_{i,i}$) is less than -25% within one year post the release of 10-K filings. Even though -25% threshold is arbitrary, it is well below than -10% to secure an extreme price drop. The results are robust to various cutoffs, both higher and lower, and to different measures of returns such as raw returns, market- or industry-adjusted returns, or market-model excess returns.

Compared to *shockff3* which is still influenced by an industry factor, the second and alternative crash risk measure (*crash*) is based on the firm-specific weekly abnormal return that is net of market and industry influences (Hutton, Marcus, and Tehranian, 2009). Specifically, I define the firm-specific weekly return, denoted by W, as the natural logarithm of one plus the residual return from the industry-adjusted expanded market model regression below.

$$r_{j,t}=\alpha_i+\beta_{1j}r_{m,t-1}+\beta_{2j}r_{ind,t-1}+\beta_{3j}r_{m,t}+\beta_{4j}r_{ind,t}+\beta_{5j}r_{m,t+1}+\beta_{6j}r_{ind,t+1}+\varepsilon_{j,i}, \tag{3}$$

where $r_{j,t}$ is the return on stock j in week t, $r_{m,t}$ is the return on the CRSP value-weighted market index in week t, and $r_{ind,t}$ is the industry return based on Fama-French 49 industry classification. I include the lead and lag terms for the market and industry returns to allow for nonsynchronous trading. The firm-specific weekly return for firm j in week t, $W_{j,t}$, is measured as ln(1+ $\varepsilon_{j,t}$) from Equation (3). *crash* is defined as the occurrence of any week with the firm-specific return ($W_{j,t}$) exceeding 3.09 standard deviations below its mean value within one year post the release of 10-K filings. The choice of 3.09 is meant to generate a frequency of 0.1% in the normal distribution. See Appendix 4 for variable definitions.

In sum, a major difference between two firm-specific abnormal returns, i.e., *shockff3* and *crash* is that the first is influenced by an industry factor, whereas the latter is influenced by a size and value factor.

3.4 Regression specification

To examine whether environmental information disclosed in 10-Ks is bad news, I regress the measure of short-term market reaction on environmental disclosure as follows.

$$car5_{i,t} = \beta_0 + \beta_1 env_{i,t} + \sum_{m=2}^{M} \beta_m X_{i,t} + \mu_j + \eta_t + \varepsilon_t \qquad (4)$$

where i stands for firm, j for industry, and t for time. The vector of control variables is denoted by $X_{i,t}$, which includes return (*ret*), return volatility (*stdret*), trading volume (*turnover*), size (*logat*), growth (*mb*), profitability (*roe*), leverage (*leverage*), proportion of institutional investors' holding (*iholding*), rate of litigation-related words (*litigious*), membership of environmental-sensitive industry (*esi*), other CSR-dimensions (*hrtotwords*, *retotwords*, and *sototwords*), and total number of words in a 10-K (*totwords*). Following crash risk literature, $X_{i,t}$ also includes the negative of the third moment of firm-specific weekly returns (*ncskewlag*), and earnings management level (*em*). The control variables are explained below in detail since the crash risk effect of environmental disclosure is the main research question. β_1 in the regression is the coefficient of interest, which measures the impact of *env* on *car5*.

For the impact of environmental disclosure on crash risk, I regress a dependent variable of crash risk on a measure of environmental disclosure. I add the event return, *car5*, to control variables from the market reaction model above that might affect a firm's downside risk. The baseline regression model is as follows,

$$dependent_{i,t+1} = \beta_0 + \beta_1 \sum_{m=2}^{M} \beta_m indep_{i,t} + \sum_{n=m+1}^{N} \beta_n X_{i,t} + \mu_j + \eta_t + \varepsilon_t \quad (5)$$

where the dependent variable (*dependent*) is one of the proxies for crash risk (i.e., *shockff3* and *crash*) measured in year *t+1*. The key variable of interest (*indep*) is one of the proxies for environmental disclosure (i.e., *env*, Δ*env*, *envdum*, and *envres*). The rest of variables control for factors which influence dependent variables.

All the regressions include industry dummies denoted as μ_j and year dummies denoted as η_t to control for unobserved time-invariant industry and year factors. Industry indicator variables are based on the 24 Global Industry Classification Standard (GICS) codes. In addition, standard errors are adjusted for clustering at the firm (state for the second identification strategy) and year level to control for potential bias in the estimates when the residuals of a firm are correlated across firms and years.

As for the control variables, I follow the previous literature to control for a set of factors that predict future stock price crash risk. Chen, Hong, and Stein (2001) find that firm size, past returns, and stock turnover predict crash risk. Hence, I control for firm size (*logat*) in year *t*, returns (*ret*), and trading volume (*turnover*). Similarly, I include both announcement returns (*car5*) around 10-K filings with a five-day window [-2, 2]. They also contend that more volatile stocks are more prone to a future stock price crash. Therefore, I control for stock return volatility (*stdret* and *ncskewlag*).

Hutton, Marcus, and Tehranian (2009) find that glamour stocks with a high market-to-book ratio (*mb*) have higher crash risk due to a bubble buildup in the past. Thus, I control for *mb*. They also document that crash risk is negatively related to operating performance and financial leverage but positively associated with earnings management. Accordingly, I control for profitability (*roe*), financial leverage (*leverage*), and earnings management (*em*).

Andreou, Antoniou, Horton, and Louca (2016) find that effective corporate governance mechanisms are associated with lower firm-specific stock price crashes since they help to reduce opportunistic managerial behavior. Thus, I control for the proportion of institutional investors' holding (*iholding*).

Kasznik and Lev (1995) and Skinner (1994, 1997) show that litigation risk motivates managers to quickly reveal bad news, suggesting their less bad news hoarding tendency leading to less crash risk. Therefore, I control for the level of litigation risk (*litigious*) using the proportion of litigation-related words relative to the total words in a 10-K.

Following Cho and Patten (2007) who document that firms in the environment-sensitive industry (*esi*) tend to provide more environmental disclosure, I control for the membership of *esi*.

Neu, Warsame and Pedwell (1998) argue the complementary role of other social disclosures to environmental disclosure in 10-Ks because they help to frame the interpretation of environmental disclosure. Accordingly, I additionally control for the other dimensions of corporate social responsibility (CSR) disclosures on human rights (*hrtotwords*), product responsibilities (*retotwords*), and society (*sototwords*) which influence the level of environmental disclosure.

I also control for qualitative factors on the crash risk using the number of total words in a 10-K (*totwords*). All the independent variables are measured in year *t* while the dependent variables are measured in year *t+1*. All continuous variables are winsorized at 1 and 99 percentiles to reduce the effect of outliers. Appendix 4 provides variable definitions.

3.5 Sample construction

I download all 10-Ks from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database filed from January 1998 through March 2013. Based on Campbell, Chen, Dhaliwal, Lu, and Steele (2014), I construct the sample as follows:

1) I exclude 10-Ks with less than 1,000 words, and late fillings such as NT 10-K, NT 10-KA, and NTN 10-K under Rule 12b25 of inability to timely file all or part of the 10Ks.
2) EDGAR identifies firms that file 10-Ks using Central Index Key (CIK). To match CIK and filing dates from 10-Ks with PERMNO and filing dates from the CRSP-COMPUSTAT merged data, I use the Wharton Research Data Services (WRDS) CIK-PERMNO file. I exclude all firms for which I am not able to match CIK to GVKEYs and the filing dates.
3) I exclude all firms without relevant fundamentals and stock market data from COMPUSTAT and CRSP. I also exclude all firms which have data less than 15 weeks per year.
4) I limit returns between -1 and 2. The final sample contains 81,826 firm-year observations and 9,799 unique firms between January 1998 and March 2013.

4. Empirical results

4.1 Descriptive statistics

Table 1, Panel A, reports the descriptive statistics for the main variables. In the sample, the mean values of *shockff3* and *crash* are 0.201 and 0.295, respectively. This suggests that the unconditional probabilities of a firm's stock price crash risk over a year are around 20% to 30%

similar with previous crash risk literature. Meanwhile, disclosed environmental information accounts for 0.08% of the total information in the annual report, whereas litigation-related information for 1.2%. 14% of the sample belongs to the industries sensitive to environment.

Panel B of Table 1 shows the distribution of the sample by year between 1998 and 2013. The mean number of a firm's 10-K filings gradually decreases. The mean value of environmental disclosure decreases until 2005, and then increases to the highest level of 0.1% in 2013. Specifically, its increase never stops after the legal standing of emissions and climate change in Massachusetts v. U.S. Environmental Protection Agency (EPA) in 2007. Moreover, the largest increase is recorded in 2010 when BP's Deepwater Horizon drilling rig is exploded in the Gulf of Mexico in April 2010. Thus, the year distribution provides two exogenous shocks to mitigate endogeneity and further identify a potential causality.

The mean values of *shockff3* reach to the highest points during the pinnacles of market crashes in 2001 and 2008. The mean values of *crash* have a similar trend with *shockff3*. Figure 1 graphically shows the negative association between environmental disclosure (*env*) and crash risk (*shockff3*), providing initial evidence that the more environmental disclosure, the less future crash risk.

Panel C of Table 1 summarizes the sample distribution by 24 industry groups based on the Global Industry Classification Standard (GICS) codes. Similar with Figure 1, Figure 2 graphically displays the negative relationship between environmental disclosure (*env*) and crash risk (*shockff3*). Specifically, utilities, materials, and energy are the top three industries in terms of environmental disclosure. On average, they account for 0.3%, 0.27%, and 0.23% of *env*, respectively, which is about three times higher than 0.09% of its mean value. They tend to have less mean values of crash risk proxies compared to industries with less environmental disclosure.

This implies that if a firm belongs to an industry with more environmental disclosure, it is less likely to experience stock price crash in the future.

Meanwhile, utilities have the highest environmental disclosure, whereas banks have the lowest with the least crash risk. This suggests that they are regulated and even protected by government, and provides the rationale for a robustness test after excluding them from the sample.

Panel D of Table 1 displays the Pearson correlation matrix of the main variables. As expected, two measures of crash risk are positively correlated with 0.351 of coefficient, suggesting that these measures capture the overlapping but different aspects of the skewness in return distributions, i.e., crash. As expected, the level measure of environment disclosure (*env*) is significantly and negatively correlated to all crash risk measures, suggesting that high environment disclosure firms are less likely to experience sudden stock price drop in the future.

4.2 Univariate test

Table 2 shows the mean comparisons of crash measures (*shockff3* and *crash*) based on the median value of environmental disclosure, *envdum* equal to one if *env* is above its median, and zero otherwise.

As *envdum* increases, *shockff3* significantly decreases, whereas *crash* is not significant. As in the descriptive statistics in Table 1, this provides additional initial evidence that the greater environmental disclosure, the less crash risk in the future.

4.3 Determinants of environmental disclosure

To identify the determinants of environmental disclosure, I regress *env* on the same explanatory variables from Equation (4) after replacing *stdret* with *stdretpre12* and excluding *ncskewlag* and *em*. The regression model is as follows,

$$env_{i,t} = \beta_0 + \sum_{m=1}^{M} \beta_m X_{i,t} + \mu_j + \eta_t + \varepsilon_t \quad (6)$$

where i stands for firm and t for time. The vector of control variables is denoted by $X_{i,t}$, which includes return (*ret*), previous return volatility (*stdretpre12*), trading volume (*turnover*), size (*logat*), growth (*mb*), profitability (*roe*), leverage (*leverage*), proportion of institutional investors' holding (*iholding*), proportion of litigation-related words (*litigious*), membership of environmental-sensitive industry (*esi*), other CSR-dimensions (*hrtotwords*, *retotwords*, and *sototwords*), and total number of words in a 10-K (*totwords*). The model includes industry fixed effect to account for cross-industry differences and year fixed effect to control for common time trends. Standard errors are cluster-adjusted at firm and by year levels. All continuous variables are winsorized at 1 and 99 percentiles to reduce the effect of outliers. Appendix 4 provides variable definitions.

Table 3 reports OLS regression results on the determinants of environmental disclosure. Consistent with previous literature (e.g., Neu, Warsame and Pedwell, 1998), environmental disclosure is positively associated with firm size (*logat*) and the membership of environment-sensitive industry (*esi*). Previous literature documents the mixed results on its relationship with profitability (*roe*) and leverage (*leverage*). The results show its positive correlation with *leverage*, *ret*, *hrtotwords*, and *totwords*, while its negative association with *stdretpre12*, *turnover*, and *retotwords*. Particularly, its positive correlation with *litigious* suggests that environmental disclosure is closely related to litigation risk of which tone is mostly negative, implying that it is bad news which managers tend to hide.

4.4 Evidence of Environmental Disclosure as Bad News

To test the hypotheses, it is crucial to show that environment information disclosed in 10-Ks is bad news since the link between environmental disclosure and crash risk is explained only by managers' bad news hoarding tendency. Specifically, if environmental information is bad news, then managers tend to hide it for an extended period until it is abruptly revealed to the public, leading to a significant drop in stock price. In other words, their lower tendency of bad news hoarding is highly likely to reduce the future crash risk. Thus, to show that disclosed environmental information is bad news, the study implements a battery of tests.

First, the research shows the positive relationship of environmental disclosure with litigation risk of which tone is mostly negative, providing evidence that the former is bad news related to litigation. Panel A of Table 4 reports confirms this by showing the positive association between environmental disclosure (*env*) and litigation risk (*litigious*). Panel B of Table 4 presents the results of the univariate test on mean comparisons of environmental disclosure measure (*env*) based on the median value of *litigious* (*litigiousdum*). *litigiousdum* is equal to one if *litigious* is above its median, and zero otherwise. The results show that as *litigious* increases, *env* also significantly increases. As described in Section 4.3, Table 3 reports the positive association between *env* and *litigious* after controlling for various variables. The results suggest that disclosed environmental information is litigious-related and thus, negative news for a firm to hide.

Compared to good news relatively quickly disclosed by managers, bad news tends to be concealed. Accordingly, less disclosure of bad news will revert to the mean, i.e., mean reverting by more disclosure of it in the future. In other words, if disclosed environmental information is bad news, then it will be mean reverting. Panel C of Table 4 shows the results of the mean reversal of the change values in environmental disclosure. Δ*envlag* (Δ*envlead*) is the difference between Δ*env* and previous (next)-period Δ*env*. Δ*env* is negatively associated with both Δ*envlag* and Δ*envlead*, supporting its mean reversal. This suggests that disclosed environmental information is bad news.

Panel D of Table 4 provides direct evidence that disclosed environmental information is bad news by comparing the relative proportion of the number of negative (*envneg*) and positive (*envpos*) environment-related keywords to the number of total environmental-related keywords when the number of total environmental-related words is greater than 0 in a 10-K filing in year t. The summary statistics show that the negative environmental information is more disclosed than the positive one by 1.2%, i.e., 3.4% vs. 2.2%.

Overall, the results suggest that disclosed environmental information is bad news, supporting managers' bad news hoarding tendency related to future crash risk.

4.5 Environment disclosure and short-term market reaction

Market negatively reacts to bad news. As shown in Section 4.4, if disclosed environmental information is bad news, then investors show a negative reaction to it. Consistent with this, the results of Table 5 display the significantly negative association between *env* and *car5* at $p<0.05$ after controlling for various factors across models. Thus, the results confirm the first hypothesis. *car5* is cumulative abnormal returns above value-weighted market returns for 5 trading days around a 10-K filing date (i.e., -2 to +2 with day 0 as the filing date).

4.6 Environment disclosure and crash risk

Table 6 reports the logit regression results of the impact of environmental disclosure on crash risk. In Columns (1) to (2), the dependent variable is *shockff3* which is an indicator equal to one if there is any week during which the abnormal return based on Fama-French three-factor is less than -25% within one year post the release of a 10-K filing, and zero otherwise. In Columns (3) to (4), the dependent variable, *crash,* is an indicator equal to one if a firm experiences any firm-specific weekly returns exceeding 3.09 standard deviations below the mean firm-specific weekly return within one year post the release of a 10-K filing, and zero otherwise.

Across all models of Table 6, I find that *env*, which is measured as the ratio of the total number of environment-related keywords to the total number of words in 10-Ks, is negative and statistically significantly related to both measures of crash risk (*shockff3* and *crash*). Untabulated tables show that the results are robust to the model after excluding an industry fixed effect to avoid capturing the industry effect twice due to *esi*, or vice versa, whose significance is stronger in general.

Overall, the study provides empirical evidence that more environmental disclosure in 10-Ks is associated with lower future stock price crash risk. The results are consistent with the second hypothesis, suggesting that even small proportion of environmental disclosure with average 0.08%.of 10K's total disclosure) is highly likely to make a significant impact on future crash risk.

To assess the economic significance of environmental disclosure, I compute the odds ratios for model (2) and (4) of Table 6 using the standard deviation reported in Panel A of Table 1. The odds ratios for a one standard deviation increase in *env* are 0.95 and 0.97 for each model, indicating that a one standard deviation increase in *env* reduces the odds of future crash risk (*shockff3* and *crash*) by 10% if I fix all the other variables at a fixed value. In comparison, a one standard deviation increase in firm size (*logat*) reduces the odds of *shockff3* and *crash* by 7% and 8%, respectively. The results suggest that the negative association between environmental disclosure and future stock price crash risk is economically significant.

Table 6 also shows that when the dependent variable is *shockff3* in Columns (1) and (2), crash risk is negatively correlated with cumulative abnormal return around the 10-K filing release date (*car5*), current return (*ret*), firm size (*at*), profitability (*roe*), and corporate governance (iholding), but positively related with stock return volatility (*stdret* and *ncskewlag*), information asymmetry level (*turnover*), financial performance (*leverage*), the total number of words in a 10-K filing (*totwords*), and the level of earnings management (*em*). When the dependent variable is *crash* in Columns (3) and (4), the coefficients on the control variables largely have a similar statistical significance with those of *shockff3*.

Meanwhile, Loughran and McDonald (2014) find that a 10-K filing with a larger size is associated with higher volatility within one month after the filing due to its complexity. Motivated by this, Li and Zhao (2016) reveal another role of 10-K disclosures, i.e., an information role (or transparency), and document that a larger 10-K filing in two months following the filing is associated with a bigger reduction in volatility. [20] In Table 6, however, the positive association between crash risk measures (*shockff3* and *crash*) and a file size proxy (*totwords*) supports more information asymmetry due to the complexity of 10-Ks in a longer term, i.e., up to one year after the filing, inconsistent with the findings of Li and Zhao (2016).

5. Robustness checks

In this section, I implement a battery of robustness tests on the results of Column (2) and (4) Table 6, and show that the results are robust to various tests. In an odd number Columns, the dependent variable is *shockff3*, while in an even number Columns, the dependent variable is *crash*.

5.1 Change, dummy, and residual variable of environmental disclosure

[20] Previous literature (e.g., Li, 2008) uses the number of 10-K words as a measure of complexity. Loughran and McDonald (2014) find that a 10-K file size is positively correlated with the number of 10-K words (0.712 of correlation coefficient).

The panel data allows us to do time-series tests to explore a directional effect and to eliminate a time-invariant effect. However, reverse causality due to self-selection may be a concern for the empirical findings. The reason is that firms with more crash likelihood are more likely to disclose environment information in 10-Ks filings. To address this endogeneity issue, I first conduct a change analysis. Specifically, I examine whether changes in environmental disclosure in 10-Ks are negatively associated with future stock price crash risk.

Column (1) and (2) of Panel A of Table 7 show that the change in environment disclosure (Δ*env*) in 10-Ks is significantly negatively related to future crash risk, consistent with the findings for the level of environmental disclosure in Table 6.

Next, I divide the sample into two groups based on a median value of *env*, and create a dummy variable, *envdum*, when the group with a higher value of *env* takes one, and zero for a lower value relative to the median of *env*. The results of Column (3) and (4) of Panel A of Table 7 are consistent with the hypothesis that more environmental disclosure results in a lower probability of stock price crash risk in the future.

Lastly, to deal with endogeneity issue that both environmental disclosure and crash risk are determined by some common uncontrolled factors, I adopt a two-stage regression approach to first estimate residual environmental disclosure (*envres*) by replicating Column (2) of Table 3, and then use *envres* to predict future crash risk. Columns (5) and (6) of Panel A of Table 7 show the regression results using the residual value of environmental disclosure (*envres*). Consistent with the results on the raw value of environmental disclosure, the coefficients on *envres* are significantly negative, confirming the second hypothesis.

Overall, the results are robust to change, dummy, and residual values of environmental disclosure.

5.2 Exclusion of Utilities and Financials

As indicated in the sample distribution by industry in Panel C of Table 1, utilities and financials are in highly-regulated industries, which might influence the findings. After excluding firms in these industries from the sample, I rerun the level models in Colum (2) and (4) of Table 6 and the change models in Colum (1) and (2) of Panel A of Table 7.

The results of Panel B of Table 7 show that the coefficients on *env* and Δ*env* are significant and negatively associated with *shockff3* and *crash* across models. This is consistent with the results based on a full sample, confirming that the findings are robust.

6. Identification strategy

So far, the study shows the negative association between the negative nature of disclosed environmental information and crash risk because of less bad news hoarding tendency by managers. In this section, the research further identifies a potential causal relationship between two using instrumental variables (IVs) described in Section 4.1.

One exogenous shock is BP's Deepwater Horizon oil spill accident in the Gulf of Mexico in April 2010. First, I create a dummy variable (*spill*) equal to one if the year is after 2010, is missing for 2010, and zero otherwise. *spill* is a legitimate instrumental variable since it is significantly related with *env* (correlation coefficient= 0.670 at the 0.1% level) but is not endogenously determined, suggesting its causal effect on *env* and thus satisfying the relevance assumption. Heflin and Wallace (2017) find that oil and gas firms increase environmental disclosure after the oil spill accident. Thus, it is reasonably assumed that *spill* affects the outcome, i.e., crash risk, only through *env*, meeting the exclusion requirement. Moreover, the exchangeability assumption is satisfied because *spill* is less likely to share common causes with crash risk. To assess the appropriateness of IV estimation, I perform post-estimation diagnostic tests. Specifically, the Wald test for the endogeneity of an instrumented variable (its null is exogeneity) indicate that it is appropriate to treat *env* as endogenous (χ^2= 66.13 (66.36), p<0.000 for a shockff3 (crash) model). The Anderson–Rubin (Wald) test for a weak-instrument as a null hypothesis suggests that *spill* is a strong instrument for *env* as indicated by the first-stage regression statistics (χ^2=75.19 (1726.29), p<0.000 for a shockff3 model and χ^2=107.95 (1494.27), p<0.000 for a crash model). The Hausman test for an overidentification test is not available because of one IV, i.e., *spill*, suggesting that the first-stage equation is exactly identified.

First, I implement a two-stage regression using the following specification:

$$env_{i,t}=\beta_0 + \beta_1 spill_{i,t} + \sum_{n=2}^{N}\beta_n X_{i,t} + \mu_j + \eta_t + \varepsilon_t$$
$$dependent_{i,t+1}=\beta_0 + \beta_1 envhat_{i,t} + \sum_{n=2}^{N}\beta_n X_{i,t} + \mu_j + \eta_t + \varepsilon_t \tag{7}$$

Using an ordinary least square (OLS) regression at the first stage, I regress *env* on *spill* to get its predicted value (*envhat*) after adding *spill* to Equation (6). At the second stage, I rerun the same logit regressions in Column (2) and (4) of Table 6 using a predicted value (*envhat*) from the first stage as a main independent variable after replacing *env* with *envhat*. Column (1) of Panel A of Table 8 shows significantly positive associations between *env* and *spill*, supporting the largest increase in environmental disclosure in 2010 after the oil spill accident. On the other hand, Column (2) and (3) of Panel A of Table 8 displays the negative relationship between *env* and *shockff3* and *crash*, which is even stronger than the results of Column (2) and (4) of Table 6.

One might argue that *spill* could not meet the exclusion requirement for a valid IV. Thus, another exogenous shock is investigated as an IV, which is the legal standing of emissions and climate change in Massachusetts v. U.S. Environmental Protection Agency (EPA) in 2007 (127 Sup. Ct. 1438, 1440) in which twelve U.S. states and several cities bring a legal suit against the

EPA.[21] According to New York Times, the U.S. Supreme Court's legal decision on this legal battle is one of the most important environmental decisions in years, and renders authority to EPA to regulate the greenhouse gases.[22] As depicted in Figure 1, the constant increase in environmental disclosure after this event suggests that the legal decision affects firms' environmental disclosure policy, resulting in stronger negative relations between environmental disclosure and stock price crashes. To test this, I restrict the sample to firms in twelve states and create a dummy variable (*epa*) equal to one for the years after 2007, missing for 2007, and 0 otherwise. In order for *epa* to serve as a valid instrumental variable, it is required to meet the three assumptions described above. Specifically, *epa* is significantly related with *env* (correlation coefficient= 0.053 at the 0.1% level) but is not endogenously determined, affects crash risk only through *env*, and is not likely to share common causes with crash risk. This suggests that similarly with *spill*, *epa* is another legitimate instrumental variable. To evaluate *epa* as a valid IV, I also implement post-estimation diagnostic tests. The Wald test for endogeneity indicate that it is appropriate to treat *env* as endogenous (χ^2=38.46 (22.16), p<0.000 for a shockff3 (crash) model). The Anderson–Rubin (Wald) test for a weak-instrument suggests *spill* as a strong instrument for *env* as indicated by the first-stage regression statistics (χ^2= 34.02 (323.45), p<0.000 for a shockff3 model and χ^2= 22.78 (77.04), p<0.000 for a crash model). The Hausman test for an overidentification test is not available because of one IV, i.e., *epa*, suggesting that the first-stage equation is exactly identified.

Table 8 reports the results using the same Equation (7) after replacing *spill* with *epa* at the first model. Standard error in the first three models is adjusted for state and year-level

---

[21] Twelve states are California, Connecticut, Illinois, Maine, Massachusetts, New Jersey, New Mexico, New York, Oregon, Rhode Island, Vermont, and Washington.
[22] http://www.nytimes.com/2007/04/03/washington/03scotus.html?_r=0

clustering, whereas standard error in the rest models for firm and year-level clustering. Specifically, Column (1) and (4) of Panel B of Table 8 shows significant increase in environmental disclosure after the legal battle, whereas Column (2), (3), (5), and (6) of Panel B of Table 8 indicates that *epa* affects crash risk only through *env*. The results are similar with ones using *spill* as an instrumental variable even though *spill* increases environmental disclosure more than *epa*. The findings hold using sample restricted to firms only in Massachusetts.

Overall, the results suggest that an increase in environmental disclosure is highly likely to cause a decrease in crash risk.

7. Conclusion

In this paper, I examine the effect of environmental disclosure in 10-K filings on the likelihood of stock price crash risk in the future. Based on a large sample of 81,826 10-Ks from 9,799 unique U.S. firms between 1998 and 2013, the research identifies disclosed environmental information as bad news for managers to hide, and documents that a firm with more environmental disclosure has lower crash risk in the future. The results are statistically and economically significant across different measures of environmental disclosure and crash risk. Further analysis using instrumental variables identifies potential causation between environmental disclosure and crash risk.

The study also examines various determinants of environmental disclosure, and documents new determinants, for example, other CSR activities by showing that environmental disclosure has the positive (negative) human rights (turnover and product responsibilities).

Overall, the findings suggest that even a small proportion of environmental disclosure with average 0.08%.of 10K's total disclosure makes a statistically and economically significant impact on future crash risk. Thus, the results are consistent with the idea that firms benefit from non-financial information disclosure.

Finally, the study contributes to a rapidly growing trend on textual analysis by showing its usefulness to identify an underlying theory of managers' bad news hoarding in environmental disclosure.

References

Al-Tuwaijri, S., T. Christensen, and K.E. Hughes. 2004. The relations among environmental disclosure, environmental performance, and economic performance: a simultaneous equations approach. *Accounting Organizations and Society* 29: 447-471.

Amir, E., and B. Lev. 1996. Value-relevance of nonfinancial information: the wireless communications industry. *Journal of Accounting and Economics* 22: 3–30.

Andreou, P. C., C. Antoniou, J. Horton, and C. Louca. 2016. Corporate governance and firm specific stock price crashes. *European Financial Management* 22: 916–956.

Atkins, A.B., and E.A. Dyl. 1990. Price reversals, bid–ask spreads, and market efficiency. *Journal of Financial and Quantitative Analysis* 25: 535–547.

Belkaoui, A. 1976. The Impact of Disclosure of the Environmental Effects of Organizational Behavior on the Market. *Financial Management* 5: 26-31.

Benmelech, E., E. Kandel, and P. Veronesi. 2010. Stock-based compensation and CEO (dis) incentives. *Quarterly Journal of Economics* 125: 1769–1820.

Blacconiere, W.G. and D.M. Patten. 1994. Environmental Disclosures, Regulatory Costs, and Changes in Firm Value. *Journal of Accounting and Economics* 18: 357-377.

Blacconiere, W.G. and W.D. Northcut. 1997. Environmental Information and Market Reactions to Environmental Legislation. *Journal of Accounting, Auditing and Finance* 12: 149-178.

Bremer, M. and R.J. Sweeney. 1991. The reversal of large stock-price decreases. *Journal of Finance* 46: 747–754.

Chambers A., and S. Penman. 1984. Timeliness of reporting and the stock price reaction to earnings announcement. *Journal of Accounting Research* 21: 21–47.

Chen, J., H. Hong, and J.C. Stein. 2001. Forecasting Crashes: Trading Volume, Past Returns, and Conditional Skewness in Stock Prices. *Journal of Financial Economics* 61: 345-81.

Chen, C., J.B. Kim, and L. Yao. 2017b. Earnings smoothing: does it exacerbate or constrain stock price crash risk? *Journal of Corporate Finance* 42: 36–54.

Cho, CH, R.W. Roberts, and D.M. Patten. 2010. The language of US corporate environmental disclosure. *Accounting, Organizations and Society* 35: 431–443.

Cho, CH, and D.M. Patten. 2007. The Role of Environmental Disclosures as Tools of Legitimacy: A Research Note. *Accounting, Organizations and Society* 32: 639–647.

Deegan C. 2002. The legitimizing effect of social and environmental disclosures: a theoretical foundation. *Accounting, Auditing and Accountability Journal* 15: 282–311.

DeFond, M., M. Hung, S. Li, and Y. Li. 2015. Does mandatory IFRS adoption affect crash risk? *The Accounting Review* 90: 265– 299.

Ertugrul, M., J. Lei, J. Qiu, and C. Wan. 2017. Annual report readability, tone ambiguity, and the cost of borrowing. *Journal of Financial and Quantitative Analysis* 52: 811-836.

Gray, R., R. Kouhy, and S. Lavers. 1995b. Corporate Social and Environmental Reporting A Review of Literature and a Longitudinal Study of UK Disclosure. *Accounting, Auditing & Accountability Journal* 8: 47-77.

Grossman, S. 1981. The Informational Role of Warranties and Private Disclosure about Product Quality. *Journal of Law and Economics* 24: 461-83.

Habib, A., H. Jiang, and M. M. Hasan. 2016. Stock price crash risk: Review of the empirical literature. *Accounting and Finance*.

Hackston, D. and M.J. Milne. 1996, Some Determinants of Social and Environmental Disclosures in New Zealand Companies, *Accounting, Auditing and Accountability Journal* 9:

77- 108.
Healy, P. and K. Palepu. 2001. Information asymmetry, corporate disclosure, and the capital markets: a review of the empirical disclosure literature. *Journal of Accounting and Economics* 31: 405–440.
Heflin, F. and D. Wallace. 2017. "The BP oil spill: shareholder wealth effects and environmental disclosures". *Journal of Business, Finance and Accounting* 44: 337-374.
Hughes, S.B., A. Anderson, and S. Golden. 2001. Corporate environmental disclosures: are they useful in determining environmental performance?. *Journal of Accounting and Public Policy* 3: 217–240
Hutton, A. P., A. J. Marcus, and H. Tehranian. 2009. Opaque financial reports, R^2, and crash risk.
Journal of Financial Economics 94: 67–86.
Ingram, R.W. 1978. An Investigation of the Information Content of (Certain) Social Responsibility Disclosures. *Journal of Accounting Research* 16: 270-285.
Jin, L., and S. C. Myers. 2006. R^2 around the world: New theory and new tests. *Journal of Financial Economics* 79: 257–292.
Kasznik R., and B. Lev. 1995. To warn or not to warn: management disclosures in the face of an earnings surprise. *The Accounting Review* 70: 113–134.
Kim Y., H. Li, and S. Li. 2014. Corporate social responsibility and stock price crash risk *Journal of Banking Finance* 43: 1–13.
Kim, J.B., Y. Li, and L. Zhang. 2011a. Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics* 100: 639–662.
Kim, J.B., Y. Li, and L. Zhang. 2011b. CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics* 101: 713–730.
Kim, J., and Zhang, L. 2015. Accounting conservatism and stock price crash risk: Firm-level evidence. *Contemporary Accounting Research* 33: 412–44.
Kothari S.P., S. Shu, and P. Wysocki. 2009. Do managers withhold bad news? *Journal of Accounting Research* 47: 241–276.
Kross, W., and D.A. Schroeder. 1984. An empirical investigation of the effect of quarterly earnings announcement timing on stock returns. *Journal of Accounting Research* 22: 153–176.
Lee, M. T., and M. T. Lee. 2016. Corporate social responsibility and stock price crash risk: evidence from an Asian emerging market. *Managerial Finance* 42: 963–979.
Lev, B. 1988. Toward a Theory of Equitable and Efficient Accounting Policy. *The Accounting Review* 68: 1-22.
Li, F. 2008. Annual Report Readability, Current Earnings, and Earnings Persistence. *Journal of Accounting and Economics* 45: 221–47.
Li, Y., G.D. Richardson, and D.B. Thornton. 1997. Corporate Disclosure of Environmental Liability lnformation: Theory and Evidence. *Contemporary Accounting Research* 14: 435-474.
Loughran, T., and B. McDonald. 2014. Measuring Readability in Financial Disclosures. *Journal of Finance* 69: 1643–71.
Lu, J., and K. Nakajima. 2014. Corporate social responsibility and crash risk for Japanese firms. working paper, Nikko Financial Intelligence Inc., Tokyo, November 11.
Milgrom, P. 1981. Good News and Bad News: Representation Theorems and Applications. *Bell Journal of Economics* 12: 380-91.
Nagar, V., D.J. Nanda, and P. Wysocki. 2003. Discretionary disclosure and stock-based incentives. *Journal of Accounting and Economics* 34: 283–309.

Neu, D., H. Warsame, and K. Pedwell. 1998. Managing public impressions: environmental disclosures in annual reports. *Accounting Organizations and Society* 23: 265-282.
Pae, S. 2005. Selective disclosures in the presence of uncertainty about information endowment. *Journal of Accounting and Economics* 39: 383-409.
Patten, D.M. 1992. Intra-Industry Environmental Disclosures in Response to the Alaskan Oil Spill: A Note on Legitimacy Theory. *Accounting, Organizations and Society* 175: 471-475.
Pritamani, M., and V. Singal. 2001. Return predictability following large price changes and information releases. *Journal of Banking and Finance* 25: 631–656.
Richardson, A. J. and M. Welker. 2001. Social Disclosure, Financial Disclosure and the Cost of Capital. *Accounting, Organizations and Society* 26: 597-616.
Savor, P. G. 2012. Stock returns after major price shocks: The impact of information. *Journal of Financial Economics* 106: 635 – 659.
Securities and Exchange Commission (SEC). 1998. A Plain English Handbook: How to Create Clear SEC Disclosure Documents (U.S. Securities and Exchange Commission, Washington, DC).
Skinner, D. 1994. Why firms voluntarily disclose bad news. *Journal of Accounting Research* 32: 38–60.
Skinner, D. 1997. Earnings disclosures and stockholder lawsuits. *Journal of Accounting and Economics* 23: 249–283.
Villiers, C. de, and C. J. van Staden. 2011. Where firms choose to disclose voluntary environmental information. *Journal of Accounting and Public Policy* 30: 504-525.
Zhang, M., L. Xie, and H. Xu. 2016. Corporate philanthropy and stock price crash risk: evidence from China. *Journal of Business Ethics* 139: 595–617.

Appendix 1: SEC Rules on Environmental Disclosure

SEC rules on environmental disclosure in 10-Ks include Securities Act of 1933 and Securities Exchange Act of 1934 and Staff Accounting Bulletin (SAB) No. 92 on environmental liability disclosure. In particular, the most environmental related components in Regulation S-K include item 101, 103, and 303. I cite related rules on environmental disclosures as follows:

§229.101 (Item 101) Description of business.

"(xii) Appropriate disclosure also shall be made as to the material effects that compliance with Federal, State and local provisions which have been enacted or adopted regulating the discharge of materials into the *environment*, or otherwise relating to the protection of the *environment*, may have upon the capital expenditures, earnings and competitive position of the registrant and its subsidiaries. The registrant shall disclose any material estimated capital expenditures for *environmental* control facilities for the remainder of its current fiscal year and its succeeding fiscal year and for such further periods as the registrant may deem materials."

"(xi) Costs and effects of compliance with *environmental* laws (federal, state and local)."

§229.103 (Item 103) Legal proceedings.

"5. Notwithstanding the foregoing, an administrative or judicial proceeding (including, for purposes of A and B of this Instruction, proceedings which present in large degree the same issues) arising under any Federal, State or local provisions that have been enacted or adopted regulating the discharge of materials into the *environment* or primary for the purpose of protecting the environment shall not be deemed "ordinary routine litigation incidental to the business" and shall be described if:…"

§229.303 (Item 303) Management's discussion and analysis of financial condition and results of operations.
"(a) Full fiscal years. Discuss registrant's financial condition, changes in financial condition and results of operations."

Appendix 2: Top-50 Most Frequent Environment-related Keywords in 10-Ks

Keywords	Frequency	Keywords	Frequency
environmental	115,336	reusable	3,997
hazardous	57,681	reuse	3,966
contamination	39,535	terrain	3,847
pollution	30,376	dumping	3,633
emissions	27,231	effluent	3,597
epa	22,003	terrestrial	3,526
emission	18,300	drought	3,448
contaminated	17,891	nox	3,329
groundwater	14,920	forestry	3,070
pollutants	14,913	sewage	3,010
environmentally	13,616	recycle	2,981
cercla	12,594	depleting	2,534
responsiveness	12,443	geothermal	2,399
asbestos	9,892	habitat	2,235
noise	9,371	vegetation	2,204
rcra	7,181	ghg	1,951
toxicity	6,074	sludge	1,888
subsurface	5,558	ecological	1,726
ozone	4,817	reused	1,677
wetlands	4,720	recyclable	1,571
sanitation	4,691	aerosol	1,474
endangered	4,534	biodegradable	1,444
wildlife	4,397	pathogen	1,369
sustainability	4,369	incineration	1,297
pollutant	4,294	forests	1,182

Appendix 3: Examples of Sentences containing Environment-related Keywords

Keywords	Examples
Environmental	"Future closure, reclamation and **environmental** related expenditures are difficult to estimate in many circumstances due to the early stages of investigation, uncertainties …"
Hazardous	"Some of the Company's current and former facilities are the subject of environmental investigations and remediations resulting from historical operations and the release of **hazardous** substances or other constituents."
Contamination	"The Company believes that none of its activities caused **contamination** at the Site, and will contest this claim by EPA and therefore no liability has been accrued for this matter."
Pollution	"Population growth, increasing per capita demand for electric power in emerging markets, and **pollution** from coal-fired plants further provide a strong foundation for increased demand for nuclear fuel."
EPA	"In April 2012, the **EPA** proposed new source performance standards for new fossil-fueled generating facilities that would limit emissions of carbon dioxide to 1,000 pounds per MWh."
CERCLA	"The decision establishes that Appleton is no longer a PRP, no longer liable under the federal Comprehensive Environmental Response, Compensation, and Liability Act, ("**CERCLA**" or "Superfund"),…"
Asbestos	"As discussed more fully in Note 18 of the notes to our consolidated financial statements, we are responsible for certain future liabilities relating to alleged exposure to **asbestos** containing products."
Ozone	"Until the states have developed implementation plans for the new NOx, SO2 and **ozone** standards, it is not possible to determine the impact on Dominion?"
Pollutants	"Final MACT Rule: The CAA requires the EPA to develop industry-based standards to control emissions of hazardous air **pollutants**, or HAPs."
Effluent	"Environmental Initiatives: There are proposed legislation, rules and initiatives involving matters related to air emissions, water **effluent**, hazardous materials and greenhouse gases, all of which affect generation plant capital expenditures and operating costs as well as future operational planning."
GHG	"Similar regulations exist at the federal level which require compliance related to greenhouse gas (**GHG**) emissions and also allow for the sale of excess credits by one manufacturer to other manufacturers."
Recycles	"The company manufactures and **recycles** a variety of pallets types as well as boxes."
Oil spill	"In the event of an **oil spill** or containment event, the appropriate OSRP and Containment Plan would be executed as needed."
Climate change	"The physical impacts of **climate change** present potential risks for severe weather (floods, hurricanes, tornadoes, etc.) at certain of the Company?"
Carbon dioxide	"In 2010, the most recent year reported, **carbon dioxide** (CO2), a byproduct of all sources of combustion, accounted for approximately 84 percent of total U.S."
Global warming	"Countermeasures being sought to limit **global warming** are expected to favor the deployment of alternative energy technologies."
Kyoto Protocol	"The current international climate framework, the United Nations-sponsored **Kyoto Protocol**, prescribes specific targets to reduce GHG emissions for developed countries for the 2008-2012 period."
Carbon dioxide	"Congress has considered establishing a cap-and-trade program to reduce U.S. emissions of greenhouse gases, including **carbon dioxide** and methane."
Clean Air	"The **Clean Air** Act is a federal law administered by the EPA that provides a framework for protecting and improving the nation's air quality and controlling sources of air emissions."

Appendix 4: Variable Definitions

Variable	Definition
Dependent variables: Maker reaction measure	
car5	Sum of daily market-adjusted abnormal return during five days event window around a firm's 10-K filing date (i.e., -2 to +2 with day 0 as 10-K filing date), i.e., $car5_{i,t} = \exp[\sum_{t=-2}^{2} \ln(1 + returni, t - vwretdi, t)] - 1$ where $return_{i,t}$ is the daily stock return, and $vwretd_{i,t}$ is the market return on stock i in time t.; Earning announcement dates are captured from a 10-K per se downloaded from SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database.
Dependent variables: Stock price crash risk measures	
shockff3	An indicator variable equal to one if there is any week during which the abnormal return based on Fama-French three factor model is less than -25% within one year post the release of a 10-K filing, and zero otherwise.
crash	An indicator variable equal to one if a firm experiences any firm-specific weekly returns exceeding 3.09 standard deviations below the mean firm-specific weekly return within one year post the release of a 10-K filing, and zero otherwise. The firm-specific weekly return is $W_{j,t}$=ln $(1+\varepsilon_{j,t})$, with the residual $\varepsilon_{i,t}$ estimated from the expanded market model regression: $r_{j,t}=\alpha_i+\beta_1 r_{i,t-1}+\beta_2 r_{m,t-1}+\beta_3 r_{i,t}+ \beta_4 r_{m,t}+\beta_5 r_{i,t+1}+\beta_6 r_{m,t+1}+\varepsilon_{j,t}$, where $r_{j,t}$ is the return on stock j in week t, $r_{i,t}$ is the return on the CRSP value-weighted industry index in week t; and $r_{m,t}$ is the return on the CRSP value weighted market index in week t.
Environmental disclosure variables	
env	100*the ratio of the number of environment-related keywords to the total number of words in a 10-K filing in year t.
Δ*env*	The change in the total number of environment-related keywords from year t, scaled by the average number of environment-related keywords in the 10-K filings in year t and year t-1, namely, Δenv_t=2*$(\Delta env_t$-$\Delta env_{t-1})/(\Delta env_t+\Delta env_{t-1})$.
envlagchg	The change in the total number of environment-related keywords from year t-1, scaled by the average number of environment-related keywords in the 10-K filings in year t-1 and year t-2, namely, Δenv_t=2*$(\Delta env_{t-1}$-$\Delta env_{t-2})/(\Delta env_{t-1}+\Delta env_{t-2})$.
envleadchg	The change in the total number of environment-related keywords from year t+1, scaled by the average number of environment-related keywords in the 10-K filings in year t+1 and year t, namely, Δenv_t=2*$(\Delta env_{t+1}$-$\Delta env_t)/(\Delta env_{t+1}+\Delta env_t)$.
envdum	Equal to one if the number of environment-related keywords in a 10-K filing is above its median, and zero otherwise in year t.
envres	The number of abnormal environmental disclosure equal to residuals from regressing env_t on control variables in year t.
envneg	The ratio of the number of negative environment-related keywords to the number of total environmental-related keywords when the number of total environmental-related words is greater than 0 in a 10-K filing in year t.
envpos	The ratio of the number of positive environment-related keywords to the number of total environmental-related keywords when the number of total environmental-related words is greater than 0 in a 10-K filing in year t.
Control variables	
logat	The natural logarithm of one plus the total assets over the fiscal year period t.
ret	Average of daily returns over the fiscal year period t.
stdret	The standard deviation of daily returns over the fiscal year period t.
stdretpre12	The standard deviation of daily returns over the fiscal year period t-1.
mb	The ratio of Market value of equity to book value of equity in year t.
roe	The ratio of income before extraordinary items (IB) to common/ordinary equity in year t.

leverage	The ratio of total long-term debts to total assets in year t.
intangible	The ratio of intangible assets to total assets in year t.
iholding	Institutional holding is measured as the total number of shares held by institutions divided by shares outstanding at the end of the same quarter in quarter t. The percentage holdings of institutional investors are zero if no institutional investor reports positive holdings for a firm-quarter.
totwords	The natural logarithm of one plus the number of total words in 10-Ks in year t.
turnover	Share trading volume, calculated as 100 times the number of shares traded for a firm deflated by the total number of common shares outstanding in year t.
litigious	The ratio of the number of litigation-related keywords to the total number of words in a 10-K filing in year t.
esi	Equal to one if a firm belongs to an environmentally sensitive industry which has the 2-digit SIC code such as 13 (oil exploration), 26 (paper), 28 (chemical and allied products), 29 (petroleum refining), or 33 (metals), and zero otherwise.
hrtotwords	The natural logarithm of one plus the total number of human right–related keywords in a 10-K filing in year t.
retotwords	The natural logarithm of one plus the total number of product responsibility–related keywords in a 10-K filing in year t.
sototwords	The natural logarithm of one plus the total number of society–related keywords in a 10-K filing in year t.
ncskewlag	The negative skewness of firm-specific weekly returns over the fiscal year period.before the release of a 10-K filing, calculated as by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power.
em	Magnitude of Earnings management measured as the absolute value of discretionary accruals (Hutton et al. 2009)
ytrend	Year trend which is equal to the year of the 10-K filing minus 1998.
Instrument variables	
spill	BP's Deepwater Horizon oil spill accident equal to one if year is after 2010, is missing for 2010, and zero otherwise.
epa	Massachusetts v. Environmental Protection Agency lawsuit equal to one if year is after 2007, is missing for 2007, and zero otherwise.
Moderating variable	
lognanalystdum	Equal to one if lognanalyst is above its median, and 0 otherwise. lognanalyst is defined as a natural logarithm of the number of analysts following the firm in year t.
Other variable	
litigiousdum	Equal to one if *litigious* is above its median, and zero otherwise.

Table 1 Descriptive Statistics

This table reports the descriptive statistics of the 81,826 firm-year observations in the sample period 1998-2013. All continuous variables are winsorized at 1 and 99 percentiles. See Appendix 4 for all variable definitions.

Panel A: Summary Statistics

Variable	N	Mean	Std Dev	Q1	Median	Q3
shockff3	81,826	0.201	0.401	0.000	0.000	0.000
crash	81,826	0.295	0.456	0.000	0.000	1.000
env (%)	81,826	0.081	0.136	0.000	0.021	0.095
car5	81,826	-0.001	0.073	-0.032	-0.002	0.027
ret	81,826	0.001	0.002	-0.001	0.000	0.002
stdret	81,826	0.079	0.049	0.044	0.066	0.101
stdretpre12	81,826	0.039	0.024	0.022	0.032	0.049
ncskewlag	81,826	0.020	0.761	-0.417	-0.013	0.404
turnover	81,826	0.007	0.007	0.002	0.004	0.009
logat	81,826	5.994	2.103	4.442	5.968	7.424
mb	81,826	1.203	0.593	0.810	1.090	1.441
roe	81,826	-0.145	0.766	-0.099	0.065	0.136
leverage	81,826	0.548	0.278	0.326	0.540	0.760
intangible	81,826	0.121	0.174	0.000	0.032	0.183
totwords	81,826	9.623	0.754	9.217	9.746	10.161
em	81,826	0.081	0.111	0.016	0.042	0.095
iholding	81,826	0.514	0.317	0.221	0.522	0.815
litigious	81,826	0.012	0.005	0.008	0.011	0.015
risk	81,826	0.012	0.005	0.008	0.012	0.016
esi	81,826	0.139	0.346	0.000	0.000	0.000
hrtotwords	81,826	1.133	1.785	0.000	0.000	2.944
retotwords	81,826	1.229	1.855	0.000	0.000	3.091
sototwords	81,826	0.495	1.247	0.000	0.000	0.000

Panel B: Sample Distribution by Year

This panel shows the sample distribution by year of the 81,826 firm-year observations in the sample period 1998-2013. The first two in *Overall* represent the total number of observations (nobs) and firms (nfirm), respectively, and the rest are an average value for *shockff3*, *crash*, and *env*, respectively. See Appendix 4 for all variable definitions.

year	nobs	nfirm	shockff3	crash	env
1998	1,393	1,279	0.263	0.394	0.077
1999	6,911	5,894	0.303	0.326	0.086
2000	6,394	5,548	0.377	0.299	0.086
2001	6,251	5,362	0.276	0.205	0.080
2002	6,314	5,290	0.278	0.289	0.075
2003	5,958	4,916	0.121	0.169	0.074
2004	5,773	4,732	0.113	0.228	0.072
2005	5,910	4,591	0.091	0.277	0.069
2006	5,337	4,495	0.083	0.274	0.076
2007	5,249	4,426	0.182	0.518	0.075
2008	5,038	4,354	0.456	0.706	0.077
2009	4,948	4,246	0.164	0.133	0.078
2010	4,692	4,062	0.106	0.154	0.087

2011	4,394	3,876	0.126	0.329	0.093
2012	4,235	3,772	0.102	0.237	0.096
2013	3,029	2,886	0.071	0.273	0.105
Overall	*81,826*	*69,729*	*0.194*	*0.301*	*0.082*

Panel C: Sample Distribution by Industry

This panel displays the sample distribution by industry using 24 Global Industry Classification Standard (GICS) codes. See Panel B of Table 1 for *Overall*, and Appendix 4 for all variable definitions.

industry	nobs	nfirm	shockff3	crash	env
Utilities	1,813	180	0.061	0.269	0.302
Materials	3,576	409	0.154	0.309	0.270
Energy	4,899	541	0.139	0.259	0.227
Automobiles & Components	868	111	0.226	0.327	0.153
Capital Goods	5,931	654	0.167	0.296	0.145
Commercial & Professional Services	2,913	392	0.217	0.317	0.141
Transportation	1,398	164	0.157	0.310	0.131
Real Estate	3,485	387	0.076	0.300	0.115
Household & Personal Products	856	93	0.235	0.311	0.085
Food, Beverage & Tobacco	1,749	201	0.115	0.301	0.083
Consumer Durables & Apparel	3,175	389	0.218	0.320	0.067
Insurance	2,235	250	0.090	0.281	0.063
Food & Staples Retailing	651	69	0.157	0.353	0.055
Semiconductors & Semiconductor Equipment	2,252	208	0.211	0.288	0.052
Pharmaceuticals, Biotechnology & Life Sciences	5,528	634	0.344	0.323	0.051
Technology Hardware & Equipment	6,226	744	0.303	0.305	0.047
Consumer Services	2,989	338	0.163	0.290	0.040
Health Care Equipment & Services	5,901	727	0.244	0.304	0.034
Retailing	3,349	395	0.219	0.303	0.025
Telecommunication Services	1,231	198	0.335	0.339	0.025
Media	2,211	287	0.265	0.300	0.020
other	48	12	0.521	0.313	0.020
Banks	8,839	1,080	0.074	0.278	0.011
Diversified Financials	2,331	309	0.157	0.265	0.011
Software & Services	7,372	1,062	0.332	0.274	0.011
Overall	*81,826*	*9,834*	*0.207*	*0.301*	*0.087*

Panel D: Pearson Correlation Matrix of Main Variables

This panel provides the correlations among the main variables of the 81,826 firm-year observations in the sample period 1998-2013. The correlations marked in bold are significant (two-sided p < 0.05); the correlations in italics are statistically insignificant (two-sided p > 0.10). All continuous variables are winsorized at 1 and 99 percentiles. See Appendix 4 for all variable definitions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) shockff3													
(2) crash	**0.351**												
(3) env	**-0.082**	**-0.007**											
(4) car5	**-0.067**	**-0.017**	*0.006*										
(5) ret	*-0.007*	**-0.052**	*-0.004*	*0.006*									
(6) stdret	**0.435**	**-0.150**	**-0.106**	**-0.050**	**0.047**								
(7) ncskewlag	*0.004*	*-0.002*	**-0.011**	**0.011**	**-0.074**	**0.011**							
(8) turnover	**0.116**	**-0.022**	**-0.019**	**-0.037**	**0.040**	**0.255**	**0.072**						
(9) logat	**-0.270**	**0.000**	**0.158**	**0.039**	**-0.123**	**-0.454**	**0.089**	**0.143**					
(10) mb	**0.146**	**0.038**	**-0.047**	**-0.044**	**-0.017**	**0.153**	**-0.021**	**0.232**	**-0.131**				
(11) roe	**-0.276**	*0.001*	**0.074**	**0.049**	**0.107**	**-0.433**	**-0.015**	**-0.070**	**0.277**	**-0.313**			
(12) leverage	**-0.035**	*0.004*	**0.034**	**0.020**	**-0.068**	**-0.108**	**-0.020**	**-0.140**	**0.378**	**-0.047**	**-0.100**		
(13) em	**0.224**	*-0.004*	**-0.079**	**-0.036**	**0.026**	**0.367**	*-0.002*	**0.147**	**-0.313**	**0.229**	**-0.360**	**-0.092**	
(14) iholding	**-0.157**	**0.019**	**0.114**	**0.028**	**-0.076**	**-0.244**	**0.152**	**0.395**	**0.563**	**0.042**	**0.162**	**-0.030**	**-0.143**

Table 2 Univariate Mean Comparisons of Crash Measures by Median Environmental Disclosure Variable

This table shows the mean comparisons of crash measures (*shockff3* and *crash*) based on median value of environmental disclosure of the 81,826 firm-year observations in the sample period 1998-2013. *envdum* is equal to one if *env* is above its median, and zero otherwise. See Appendix 4 for all variable definitions.

	envdum=0 (A)		envdum=1 (B)		(A)-(B)
Variable	N	Mean	N	Mean	*diff.*
shockff3	40,913	0.232	40,913	0.171	0.061***
crash	40,913	0.294	40,913	0.296	-0.002

Table 3 Determinants of Environmental Disclosure

This table reports OLS regression results on the determinants of environmental disclosure.

$$env_t = \beta_0 + \sum_{m=1}^{M} \beta_m X_t + \mu_j + \eta_t + \varepsilon_t$$

All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry dummies based on 24 Global Industry Classification Standard (GICS) codes and on year dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for firm-and year-level clustering. See Appendix 4 for all variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1) env	(2) env
ret	0.593**	0.521*
	(2.08)	(1.89)
stdretpre12	-0.122***	-0.175***
	(-2.59)	(-3.71)
turnover	-0.617***	-0.720***
	(-4.37)	(-4.99)
logat	0.006***	0.004***
	(6.72)	(4.73)
mb	-0.003*	-0.002
	(-1.83)	(-1.39)
roe	-0.001	0.000
	(-0.72)	(0.34)
leverage	0.013***	0.008*
	(2.90)	(1.90)
iholding	0.005	0.003
	(1.19)	(0.64)
litigious	3.192***	3.648***
	(12.12)	(13.93)
esi	0.031***	0.032***
	(4.60)	(4.68)
hrtotwords		0.001***
		(3.23)
retotwords		-0.002***
		(-4.44)
sototwords		-0.000
		(-0.66)
totwords		0.020***
		(11.37)
constant	-0.035**	-0.211***
	(-2.36)	(-8.98)
industry f.e.	yes	yes
year f.e.	yes	yes
clustering	firm-year	firm-year
N	81,826	81,826
adj. R-sq	0.376	0.384

Table 4 Evidence of Environmental Disclosure as Bad News

Panel A: Correlation between Environmental Disclosure and Litigation

See Panel D of Table 1 for the correlation table and Appendix 4 for all variable definitions.

	env
litigious	**0.200**

Panel B: Univariate Mean Comparisons of Environmental Disclosure by Median Litigation Variable

This panel shows the mean comparisons of environmental disclosure measure (*env*) based on median value of litigation variable of the 81,826 firm-year observations in the sample period 1998-2013. *litigiousdum* is equal to one if *litigious* is above its median, and zero otherwise. See Appendix 4 for all variable definitions.

	litigiousdum=0 (A)		litigiousdum=1 (B)		(A)-(B)
Variable	N	Mean	N	Mean	*diff.*
env	40,913	0.054	40,913	0.107	-0.053***

Panel C: Mean Reversal of Change in Environmental Disclosure

See Panel D of Table 1 for the correlation table. Δ*envlag* (Δ*envlead*) is the difference between Δ*env* and previous (next)-period Δ*env*. See Appendix 4 for all variable definitions.

	Δenv	Δenvlag
Δ*env*		
Δ*envlag*	**-0.141**	
Δ*envlead*	**-0.235**	**0.104**

Panel D: Summary Statistics of Negative vs. Positive Environmental Disclosure

See Appendix 4 for all variable definitions.

Variable	N	Mean	Std Dev	Q1	Median	Q3
envneg	24,433	0.034	0.038	0.000	0.023	0.051
envpos	10,918	0.022	0.023	0.007	0.013	0.026

Table 5 Environmental Disclosure and Market Reaction

This table shows logit regression results on the impact of environmental disclosure on crash risk.

$$car5_{i,t} = exp[\sum_{t=-2}^{2} ln(1 + returni,t - vwretdi,t)] - 1$$

$$car5_{i,t} = \beta_0 + \beta_1 env_{i,t} + \sum_{m=2}^{M} \beta_m X_{i,t} + \mu_j + \eta_t + \varepsilon_t$$

All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry dummies based on 24 Global Industry Classification Standard (GICS) codes and on year dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for firm-and year-level clustering. See Appendix 4 for all variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1) car5	(2) car5	(3) car5
env	**-0.005****	**-0.005****	**-0.005****
	(-2.38)	**(-2.09)**	**(-2.07)**
ret	0.379	0.378	0.400
	(0.88)	(0.88)	(0.94)
stdret	-0.034	-0.032	-0.032
	(-0.92)	(-0.90)	(-0.90)
turnover	-0.339***	-0.333***	-0.330***
	(-3.82)	(-3.85)	(-3.83)
logat	0.000	0.000	0.000
	(0.00)	(0.35)	(0.23)
mb	-0.003**	-0.003*	-0.003*
	(-1.98)	(-1.95)	(-1.91)
roe	0.002**	0.002**	0.002**
	(2.55)	(2.50)	(2.52)
leverage	0.003*	0.003*	0.003*
	(1.71)	(1.73)	(1.77)
iholding	0.008***	0.008***	0.008***
	(4.80)	(4.77)	(4.71)
litigious	0.074	0.052	0.052
	(0.68)	(0.52)	(0.52)
esi	0.000	0.000	0.000
	(0.12)	(0.03)	(0.06)
hrtotwords		-0.000	-0.000
		(-0.86)	(-0.89)
retotwords		-0.000	-0.000
		(-1.13)	(-1.15)
sototwords		-0.000**	-0.000**
		(-2.15)	(-2.17)
totwords		-0.000	-0.000
		(-0.58)	(-0.55)
ncskewlag			0.001**
			(2.32)
em			-0.002
			(-0.60)
constant	0.000	0.003	0.003
	(0.02)	(0.16)	(0.18)
industry f.e.	yes	yes	yes
year f.e.	yes	yes	yes
clustering	firm-year	firm-year	firm-year

N	81,826	81,826	81,826
adj. R-sq	0.007	0.007	0.007

Table 6 Impact of Environmental Disclosure on Crash Risk

This table reports logit regression results on the impact of environmental disclosure on crash risk.

$$dependent_{t+1}=\beta_0 + \beta_1\sum_{m=2}^{M} \beta_m indep_t + \sum_{n=m+1}^{N} \beta_n X_t + \mu_j + \eta_t + \varepsilon_t$$

In Columns (1) to (2), the dependent variable is *shockff3* which is an indicator equal to one if there is any week during which the abnormal return based on Fama-French three factor plus momentum model is less than -25% within one year post the release of a 10-K filing, and zero otherwise. In Columns (3) to (4), the dependent variable *crash* is an indicator equal to one if a firm experiences any firm-specific weekly returns exceeding 3.09 standard deviations below the mean firm-specific weekly return within one year post the release of a 10-K filing, and zero otherwise. All the independent variables are measured in year *t* while the dependent variables are measured in year *t+1*. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry dummies based on 24 Global Industry Classification Standard (GICS) codes and on year dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for firm-and year-level clustering. See Appendix 4 for all variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1) shockff3	(2) shockff3	(3) crash	(4) crash
env	**-0.429****	**-0.400****	**-0.263****	**-0.245***
	(-2.55)	**(-2.40)**	**(-1.98)**	**(-1.84)**
car5	-1.039***	-1.046***	-0.637***	-0.639***
	(-5.75)	(-5.90)	(-4.03)	(-4.08)
ret	-31.772**	-30.681**	-31.540**	-31.126**
	(-2.34)	(-2.25)	(-2.57)	(-2.54)
stdret	16.426***	16.288***	-13.767***	-13.927***
	(27.17)	(27.14)	(-11.23)	(-11.34)
turnover	15.476***	14.558***	11.765***	11.135***
	(4.02)	(3.90)	(3.44)	(3.39)
logat	-0.164***	-0.160***	-0.091***	-0.088***
	(-7.27)	(-7.28)	(-8.02)	(-7.90)
mb	0.007	0.005	-0.011	-0.015
	(0.11)	(0.09)	(-0.31)	(-0.43)
roe	-0.189***	-0.173***	-0.195***	-0.182***
	(-7.97)	(-6.94)	(-9.63)	(-8.22)
leverage	0.579***	0.572***	0.337***	0.332***
	(8.45)	(8.34)	(7.49)	(7.26)
iholding	-0.199*	-0.209*	-0.175**	-0.175**
	(-1.79)	(-1.87)	(-2.38)	(-2.44)
litigious	-6.438	-6.813	-0.112	-0.406
	(-1.31)	(-1.39)	(-0.04)	(-0.16)
esi	-0.063	-0.062	-0.060*	-0.058
	(-0.79)	(-0.77)	(-1.69)	(-1.63)
hrtotwords	-0.013*	-0.013*	-0.002	-0.002
	(-1.69)	(-1.70)	(-0.38)	(-0.35)
retotwords	0.003	0.003	-0.006	-0.006
	(0.60)	(0.55)	(-1.22)	(-1.26)
sototwords	0.010	0.009	-0.004	-0.004
	(0.74)	(0.69)	(-0.40)	(-0.44)
totwords	0.114***	0.110***	0.071***	0.069***
	(5.09)	(4.96)	(4.74)	(4.59)
ncskewlag		0.061***		0.030***
		(4.46)		(2.89)
em		0.507***		0.414***

		(3.55)		(2.99)
constant	-1.971***	-1.976***	0.695	0.695
	(-3.60)	(-3.65)	(1.38)	(1.37)
industry f.e.	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes
clustering	firm-year	firm-year	firm-year	firm-year
N	81,826	81,826	81,826	81,826
Log likelihood	-30075.527	-30049.609	-44693.934	-44678.691

Table 7 Robustness Checks

Panel A: Change, Dummy, and Residual Variable of Environmental Disclosure

This table displays logit regression results on the impact of change, dummy and residual in environmental disclosure on crash risk. This table replicates the results of Column (2) and (4) of Table 6 using the change, dummy, and residual values of *env*. See Table 7 for the specification. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry dummies based on 24 Global Industry Classification Standard (GICS) codes and on year dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for firm-and year-level clustering. See Appendix 4 for all variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	shockff3	crash	shockff3	crash	shockff3	crash
∆env	**-0.059***	**-0.086***				
	(-1.78)	**(-1.91)**				
envdum			**-0.131*******	**-0.074*******		
			(-3.49)	**(-3.31)**		
envres					**-0.364***	**-0.264***
					(-1.89)	**(-1.77)**
car5	-1.172***	-5.912***	-1.044***	-0.638***	-1.046***	-0.639***
	(-8.48)	(-8.54)	(-5.91)	(-4.05)	(-5.89)	(-4.07)
ret	-43.732***	-374.609***	-30.723**	-31.161**	-30.824**	-31.199**
	(-3.08)	(-5.51)	(-2.25)	(-2.54)	(-2.25)	(-2.54)
stdret	16.270***	-120.464***	16.277***	-13.940***	16.295***	-13.926***
	(26.22)	(-9.82)	(27.04)	(-11.36)	(27.14)	(-11.33)
ncskewlag	0.051***	0.188***	0.060***	0.030***	0.061***	0.030***
	(3.19)	(4.51)	(4.36)	(2.84)	(4.47)	(2.88)
turnover	12.143***	81.693***	14.370***	10.997***	14.579***	11.113***
	(3.31)	(6.06)	(3.84)	(3.36)	(3.90)	(3.38)
logat	-0.172***	-0.827***	-0.159***	-0.088***	-0.163***	-0.090***
	(-7.13)	(-10.51)	(-7.24)	(-7.80)	(-7.10)	(-7.68)
mb	-0.045	-0.727***	0.006	-0.014	0.005	-0.015
	(-0.74)	(-19.09)	(0.09)	(-0.40)	(0.08)	(-0.44)
roe	-0.188***	-1.851***	-0.172***	-0.182***	-0.173***	-0.182***
	(-6.99)	(-27.67)	(-6.94)	(-8.28)	(-6.94)	(-8.22)
leverage	0.594***	3.883***	0.566***	0.329***	0.572***	0.334***
	(6.63)	(8.53)	(8.20)	(7.10)	(8.33)	(7.36)
em	0.481***	3.150***	0.498***	0.412***	0.510***	0.414***
	(3.46)	(4.71)	(3.52)	(3.01)	(3.57)	(2.99)
iholding	-0.204*	-1.261***	-0.212*	-0.175**	-0.209*	-0.174**
	(-1.91)	(-4.55)	(-1.90)	(-2.44)	(-1.87)	(-2.43)
litigious	-5.326	-9.433***	-7.757*	-1.078	-6.988	-0.372
	(-1.13)	(-2.83)	(-1.66)	(-0.44)	(-1.43)	(-0.14)
esi	-0.051	-0.366***	-0.064	-0.061*	-0.063	-0.058
	(-0.60)	(-5.41)	(-0.80)	(-1.74)	(-0.80)	(-1.63)
hrtotwords	-0.010	0.026***	-0.013*	-0.002	-0.013*	-0.002
	(-1.27)	(3.93)	(-1.70)	(-0.37)	(-1.71)	(-0.34)
retotwords	0.007	-0.054***	0.003	-0.006	0.003	-0.006
	(1.04)	(-6.44)	(0.51)	(-1.23)	(0.57)	(-1.26)
sototwords	0.015	-0.038***	0.008	-0.005	0.009	-0.004

	(0.82)	(-4.05)	(0.63)	(-0.50)	(0.69)	(-0.44)
totwords	0.140***	0.634***	0.119***	0.072***	0.110***	0.069***
	(4.61)	(6.27)	(5.25)	(4.86)	(4.86)	(4.54)
constant	-2.494***	-7.917***	-2.006***	0.691	-1.966***	0.695
	(-3.77)	(-5.10)	(-3.72)	(1.36)	(-3.63)	(1.37)
industry f.e.	yes	yes	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes	yes	yes
clustering	firm-year	firm-year	firm-year	firm-year	firm-year	firm-year
N	62,013	62,013	81,826	81,826	81,826	81,826
Log likelihood	-22321.023	-33825.453	-30042.922	-44676.881	-30051.459	-44678.375

Panel B: Exclusion of Utilities and Financials

This table shows logit regression results of the level (change) of (in) environmental disclosure on crash risk. This table replicates the results of Column (2) and (4) of Table 6 using sample excluding both utility and financial industries. See Table 7 for the specification. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry dummies based on 24 Global Industry Classification Standard (GICS) codes and on year dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for firm- and year-level clustering. See Appendix 4 for all variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)
	shockff3	crash	shockff3	crash
env	**-0.431*** **	**-0.272***		
	(-2.75)	**(-1.75)**		
∆*env*			**-0.080*** **	**-0.103***
			(-2.22)	**(-1.67)**
car5	-0.910***	-0.614***	-1.069***	-4.426***
	(-4.37)	(-3.78)	(-6.41)	(-5.28)
ret	-22.500**	-25.572**	-35.351***	-249.826***
	(-2.06)	(-2.56)	(-3.11)	(-3.42)
stdret	14.631***	-14.731***	14.822***	-102.736***
	(24.66)	(-13.19)	(22.08)	(-5.32)
ncskewlag	0.056***	0.025**	0.053***	0.167***
	(3.88)	(2.32)	(3.13)	(7.63)
turnover	15.401***	11.805***	12.338***	68.506***
	(4.22)	(3.83)	(3.45)	(4.70)
logat	-0.177***	-0.102***	-0.192***	-0.765***
	(-6.93)	(-8.43)	(-7.11)	(-5.38)
mb	0.042	-0.001	-0.010	-0.478***
	(0.73)	(-0.03)	(-0.17)	(-5.38)
roe	-0.144***	-0.161***	-0.163***	-1.424***
	(-6.19)	(-7.22)	(-5.90)	(-9.47)
leverage	0.578***	0.344***	0.579***	2.832***
	(9.71)	(5.94)	(8.22)	(5.38)
em	0.516***	0.407***	0.515***	2.346***
	(3.75)	(3.14)	(3.99)	(3.86)
iholding	-0.218**	-0.175**	-0.177	-0.738**
	(-2.03)	(-2.17)	(-1.58)	(-2.21)
litigious	-4.666	0.613	-4.624	2.088
	(-0.98)	(0.23)	(-1.16)	(0.37)

esi	-0.072	-0.003	-0.060	0.060
	(-1.15)	(-0.08)	(-0.91)	(0.50)
hrtotwords	-0.011	0.000	-0.005	0.055*
	(-1.25)	(0.04)	(-0.57)	(1.71)
retotwords	0.003	-0.006	0.008	-0.062*
	(0.54)	(-1.04)	(1.10)	(-1.67)
sototwords	0.006	-0.007	0.013	-0.049**
	(0.42)	(-0.62)	(0.80)	(-2.09)
totwords	0.125***	0.099***	0.162***	0.675***
	(4.55)	(4.12)	(4.27)	(3.54)
constant	-2.023***	0.500	-2.575***	-11.737***
	(-3.55)	(0.93)	(-3.53)	(-4.10)
industry f.e.	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes
clustering	firm-year	firm-year	firm-year	firm-year
N	60,037	60,037	46,968	46,968
Log likelihood	-24916.159	-33407.873	-18632.895	-26087.970

Table 8 Identification Strategy

Panel A: 2-Stage Regression of 2010 BP's Deapwater Horizon Oil Spill

Using with *spill* as the instrumental variable in the first stage, this table reports two-stage regression results of estimated environmental disclosure (*envhat*) on crash risk (*shockff3* and *crash*).

$$env_{i,t}=\beta_0 + \beta_1 spill_{i,t} + \sum_{n=2}^{N}\beta_n X_{i,t} + \mu_j + \eta_t + \varepsilon_t$$

$$dependent_{i,t+1}=\beta_0 + \beta_1 envhat_{i,t} + \sum_{n=2}^{N}\beta_n X_{i,t} + \mu_j + \eta_t + \varepsilon_t$$

This table replicates the results of Column (2) of Table 3 after adding *spill* after adding *spill* for the first stage OLS regression of Column (1) of Table 8, and Column (2) and (4) of Table 6 after replacing *env* with *envhat* for the second stage logit regression of Column (2) and (3) of Table 8, respectively. See Equation (5) and (6) for the specifications. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry dummies based on 24 Global Industry Classification Standard (GICS) codes and on year dummies are not reported for brevity. Wald χ^2test is for endogeneity of *env*. Anderson–Rubin (Wald) χ^2 test is for strength of *spill* as an IV. The Hausman test for an overidentification test is not available because of one IV, i.e., *spill*. The *t(z)*-statistics in parentheses for OLS (Logit) are based on standard errors adjusted for firm-and year-level clustering. See Appendix 4 for all variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)
	ols	logit	logit
	1st stage	2nd stage	2nd stage
	env	shockff3	crash
spill	0.023***		
	(5.23)		
envhat		**-1.201*** **	**-1.656*** **
		(-5.96)	**(-5.95)**
ret	0.174	9.986	1.011
	(0.49)	(0.73)	(0.08)
stdretpre12	-0.070		
	(-1.16)		
car5		-0.971***	-0.620***
		(-5.63)	(-3.88)
stdret		11.352***	-18.595***
		(9.99)	(-11.67)
ncskewlag		0.063***	0.035***
		(4.60)	(4.34)
em		0.551***	0.425***
		(3.78)	(3.03)
turnover	-0.817***	-1.511***	-1.247***
	(-6.22)	(-5.26)	(-5.33)
logat	0.004***	0.713***	0.622***
	(5.07)	(4.65)	(5.44)
mb	-0.002	-0.266***	-0.253***
	(-0.96)	(-4.10)	(-4.59)
roe	0.001	0.105	0.034
	(1.29)	(1.59)	(0.80)
leverage	0.008*	2.251***	1.705***
	(1.87)	(8.99)	(7.48)
iholding	0.005	0.877***	0.693***
	(1.06)	(4.47)	(4.27)
litigious	3.653***	7.262***	6.032***
	(13.84)	(5.83)	(5.92)

esi	0.033***	6.491***	5.318***
	(4.86)	(5.94)	(5.86)
hrtotwords	0.001***	0.249***	0.214***
	(2.99)	(5.55)	(6.26)
retotwords	-0.002***	-0.460***	-0.387***
	(-4.75)	(-5.99)	(-6.01)
sototwords	-0.000	-0.076***	-0.073***
	(-0.57)	(-5.44)	(-5.89)
totwords	0.020***	4.071***	3.325***
	(11.04)	(6.13)	(6.05)
ytrend	-0.003***		
	(-7.77)		
constant	-0.196***	-43.701***	-33.472***
	(-8.09)	(-6.19)	(-5.87)
industry f.e.	yes	yes	yes
year f.e.	no	yes	yes
clustering	firm-year	firm-year	firm-year
Wald χ^2test		66.13***	66.36***
Anderson–Rubin (Wald) χ^2test		75.19*** (1726.29***)	107.95*** (1494.27***)
N	77,134	77,134	77,134
adj. R-sq	0.379		
Log likelihood		-28646.598	-42693.087

Panel B: 2-Stage Regression of 2007 Massachusetts v. Environmental Protection Agency

Using with *epa* instead of *spill* as the instrumental variable in the first stage, this table reports two-stage regression results of estimated environmental disclosure (*envhat*) on crash risk (*shockff3* and *crash*). Sample is restricted to twelve states such as California, Connecticut, Illinois, Maine, Massachusetts, New Jersey, New Mexico, New York, Oregon, Rhode Island, Vermont, and Washington. See Panel A of Table 8, and Equation (5) and (6) for the specifications. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry dummies based on 24 Global Industry Classification Standard (GICS) codes and on year dummies are not reported for brevity. Wald χ^2test is for endogeneity of *env*. Anderson–Rubin (Wald) χ^2 test is for strength of *epa* as an IV. The Hausman test for an overidentification test is not available because of one IV, i.e., *epa*. The *t(z)*-statistics in parentheses for OLS (Logit) are based on standard errors adjusted for state (firm)-and year-level clustering. See Appendix 4 for all variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	ols	logit	logit	ols	logit	logit
	1st stage	2nd stage	2nd stage	1st stage	2nd stage	2nd stage
	env	shockff3	crash	env	shockff3	crash
epa	0.013***			0.013**		
	(3.94)			(2.56)		
envhat		**-1.245*** **	**-0.809*** **		**-1.245*** **	**-0.809*** **
		(-6.82)	**(-5.74)**		**(-5.33)**	**(-3.53)**
ret	0.597*	0.603***	0.288	0.597	0.603***	0.288
	(1.90)	(3.58)	(1.64)	(1.56)	(3.06)	(1.28)
stdretpre12	-0.113			-0.113*		
	(-1.46)			(-1.69)		
car5		-0.662**	-0.365**		-0.662***	-0.365*
		(-2.00)	(-2.32)		(-3.13)	(-1.94)
stdret		10.697***	-17.829***		10.697***	-17.829***

		(12.57)	(-15.36)		(9.48)	(-10.43)
ncskewlag		0.032	0.033		0.032	0.033*
		(1.29)	(1.52)		(1.51)	(1.77)
em		0.303	0.250		0.303	0.250
		(1.48)	(1.57)		(1.56)	(1.51)
turnover	-0.999***	-1.132***	-0.695***	-0.999***	-1.132***	-0.695***
	(-7.18)	(-6.07)	(-4.50)	(-7.55)	(-4.78)	(-2.92)
logat	0.003***	0.219***	0.150***	0.003**	0.219***	0.150**
	(3.72)	(3.90)	(3.70)	(2.36)	(2.83)	(2.25)
mb	-0.001	0.008	-0.020	-0.001	0.008	-0.020
	(-0.36)	(0.13)	(-0.43)	(-0.27)	(0.13)	(-0.48)
roe	0.001	-0.063*	-0.091***	0.001	-0.063	-0.091***
	(0.51)	(-1.78)	(-3.20)	(0.41)	(-1.64)	(-3.70)
leverage	-0.002	0.160	0.157*	-0.002	0.160	0.157
	(-0.27)	(1.62)	(1.79)	(-0.32)	(1.33)	(1.39)
iholding	0.018***	2.054***	1.216***	0.018***	2.054***	1.216***
	(2.70)	(5.22)	(4.01)	(2.84)	(4.40)	(2.73)
litigious	3.570***	4.323***	2.864***	3.570***	4.323***	2.864***
	(6.52)	(6.64)	(6.02)	(8.15)	(5.17)	(3.60)
esi	0.026*	3.262***	2.146***	0.026**	3.262***	2.146***
	(1.80)	(7.58)	(5.65)	(2.54)	(5.18)	(3.50)
hrtotwords	0.000	0.051***	0.030*	0.000	0.051***	0.030*
	(1.05)	(3.02)	(1.87)	(0.73)	(3.24)	(1.66)
retotwords	-0.003***	-0.339***	-0.222***	-0.003***	-0.339***	-0.222***
	(-6.88)	(-7.29)	(-5.25)	(-4.49)	(-5.29)	(-3.46)
sototwords	-0.000	0.010	-0.005	-0.000	0.010	-0.005
	(-0.07)	(1.04)	(-0.56)	(-0.08)	(0.76)	(-0.45)
totwords	0.016***	2.101***	1.383***	0.016***	2.101***	1.383***
	(5.10)	(7.15)	(5.97)	(7.15)	(5.62)	(3.69)
ytrend	-0.004***			-0.004***		
	(-7.82)			(-5.80)		
constant	-0.147***	-22.076***	-12.746***	-0.147***	-22.076***	-12.746***
	(-4.51)	(-6.48)	(-5.40)	(-4.96)	(-5.59)	(-3.47)
industry f.e.	yes	yes	yes	yes	yes	yes
year f.e.	no	yes	yes	no	yes	yes
clustering	state-year	state-year	state-year	firm-year	firm-year	firm-year
Wald χ^2test		38.46***	22.16***		38.46***	22.16***
Anderson–Rubin		34.02***	22.78***		34.02***	22.78***
(Wald) χ^2test		(323.45***)	(77.04***)		(323.45***)	(77.04***)
N	33,057	33,057	33,057	33,057	33,057	33,057
adj. R-sq	0.317			0.317		
Log likelihood		-12652.836	-17759.331		-12652.836	-17759.331

Figure 1 Environmental Disclosure and Stock Price Crash Risk by Year (over 1998-2013)

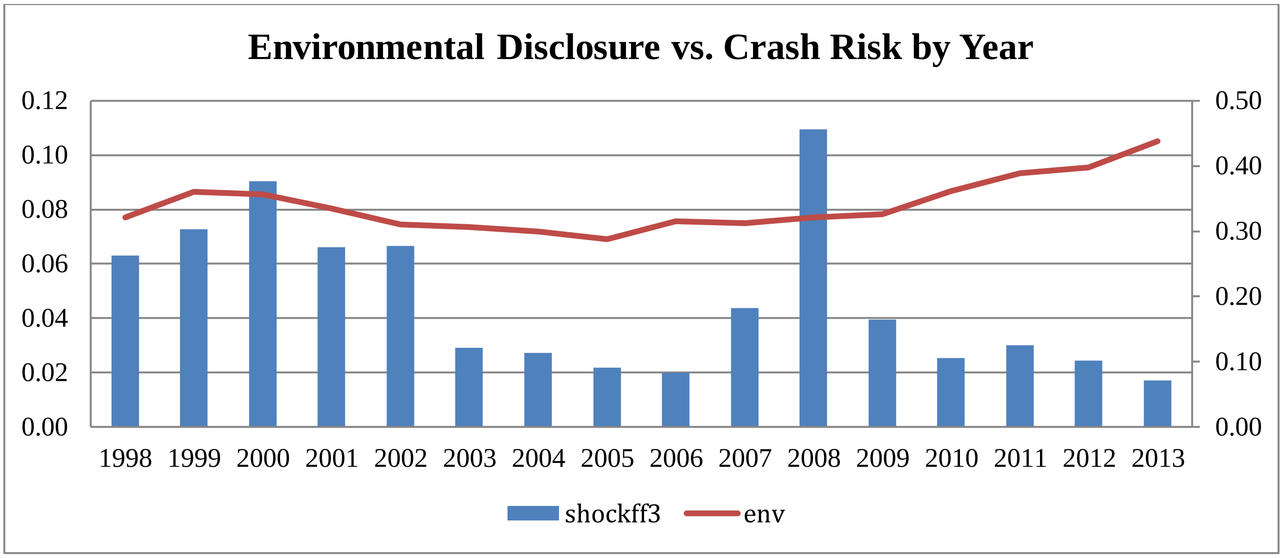
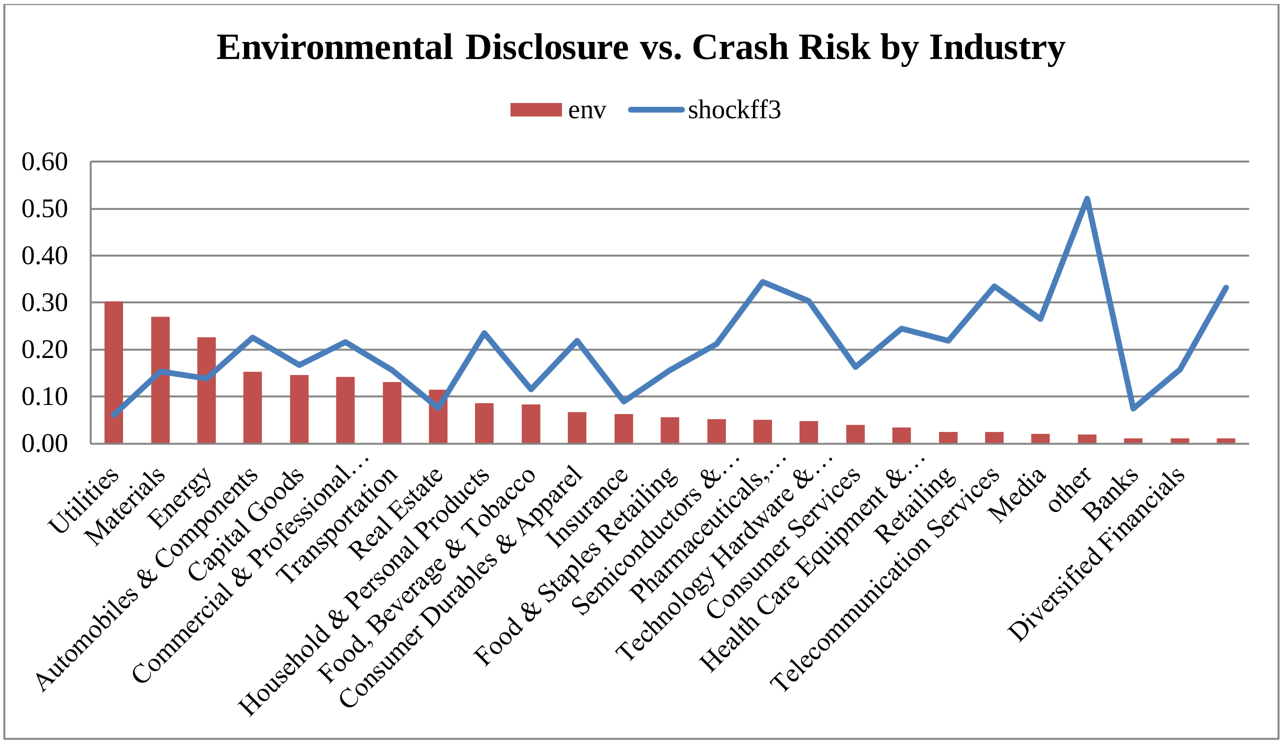


Figure 2 Environmental Disclosure and Stock Price Crash Risk by Industry (sorted by *env* over 1998-2013)



Analyst Private Research Effort, Earnings Forecast Accuracy, and Market Reaction

Abstract

The study examines the relative value of private and public information sources in analysts' earnings forecasts for U.S. firms. Using a pattern search algorithm (i.e., regular expression) on the headlines of 81,762 forecasts during 2000-2014, the research significantly improves the identification of information sources and finds that a forecast with an additional private source has a higher accuracy and stronger market reaction. Moreover, the combination of a management and non-management private source is more likely to generate the best accuracy and greatest market reaction. Finally, more accurate and informative forecasts are made by analysts with greater private research efforts even without information advantage. Overall, the study provides new insight into the determinants of forecast properties.

Keywords: Private Research Effort, Private Information Source, Earnings Forecast Accuracy, Market Reaction, Regular Expression

1. Introduction

"What is the source of that value-added?" Lo (2012) makes the question in that average equity analysts are well-paid and thus, are expected to produce significant value-added outputs.[23] [24] The research answers the question, finding that it is an additional private information source.[25]

Depending on the availability of a public information source, equity analysts include *private* (or *proprietary*) and/or *public* information as an input source of their research reports. They are well equipped with the expertise to collect and process information into various types of outputs for the report users, for example, stock recommendations, earnings forecasts, and price targets. As such, analysts play an important intermediary role between a source and a user of information.

Since those final products are potentially useful for the report users such as investors for the investment decisions, the users demand more sophisticated information from analysts. For instance, Coach, a U.S. luxury fashion firm, receives thousands of requests per year from analysts whose clients ask them to attend the firm's private events with management.[26] This anecdote suggests that proprietary information is highly regarded to be more informative by the report users, and provides a possible answer to the question from Lo (2012). Thus, it is an important empirical question on how a private information source influences analysts' performance and how the stock market reacts to it compared to a public source.

---

[23] According to Glassdoor.com, a U.S. company review site, the national average salary for an equity research Analyst is $97,014 in United States. See http://www.glassdoor.ca/Salaries/us-equity-research-analyst-salary-SRCH_IL.0,2_IN1_KO3,26.htm?countryRedirect=true.

[24] Review papers (e.g., Ramnath, Rock, and Shane, 2008; Beyer, Cohen, Lys, and Walther, 2010; Bradshaw, 2011) call for more studies to better understand the sources of analyst report value,

[25] A private (or proprietary) information source, a private (or proprietary) source, private (or proprietary) source information, private (or proprietary) information, and a private (or proprietary) research effort are interchangeably used.

[26] Refer to an article from U.S. News & World Report (https://money.usnews.com/investing/investing-101/articles/2017-08-10/stock-analysts-are-more-biased-than-you-think).

It is known that previous studies cannot precisely identify private and public information sources. To reduce the measurement error, the research employs a textual analysis technique, i.e., a regular expression for a pattern search on a headline of 81,762 analyst reports covered by 1,903 analysts from 10 global investment banks for 3,612 U.S. firms between 2000 and 2014.[27] The study finds that there is no significant difference between one private and one public information source in terms of analysts' earnings forecast error (or accuracy), but an additional proprietary source is more likely to reduce (increase) forecast error (accuracy). Regardless of the level of a private source, however, investors react more strongly to it relative to a public source. This suggests that access to a private information source requires analysts to make more research efforts (i.e., resources such as time and money) which in turn improve both their performance and the value relevance of their forecasts. This is consistent with an analyst effort hypothesis that the paper defines in Section 2.

Further analysis shows that the combination of two non-public information sources, i.e., one from management and one from non-management source, is more likely to reduce more forecast errors and to induce a stronger market reaction than any other combination. This implies that private information from non-management sources is as equally useful as that from management ones. Section 3 summarizes the classification of sources. i.e., private vs. public, and management vs. non-management. The findings are robust to different specifications using a different measure of forecast errors as well as more control variables, and to mean value regression of forecast errors.

[27] Analyst reports are those of which analysts forecast firms' earnings since the research question of interest is the accuracy of their earnings forecasts.

Besides the negative association between analysts' efforts on a private information source and forecast errors, change analyses indicate their possible causal relationship, let alone addressing an endogeneity issue due to a reverse causality as well as a time-invariant effect.

Different from the effort conjecture supported with a high effort sample (i.e., analysts initially using 0, but 1 or 2 private information sources afterward), prior research proposes the information advantage hypothesis to explain the superiority of proprietary sources relative to a public one. For example, Brown, Call, and Clement (2015) argue that analysts who work at big brokerage firms are more likely to make better forecasts because of information advantage from private phone calls with management. Therefore, the research provides fresh insight (i.e., the effort hypothesis) on the consequences of information that analysts discover from private sources not available to the public.

Additional cross-sectional analyses investigate the determinants of analysts' private research efforts. Both analyst characteristics (i.e., size of brokerage house, firm- and industry-experience, workload, forecast horizon, gender, country origin, education, and connection with covered firms) and firm characteristics (i.e., size, market value, profitability, leverage, previous return volatility, negative earnings experience, the number of analyst following, and the proportion of institutional investors' holding, trading volume, and readability of annual reports (i.e. Form 10-Ks)) are tested. The analyses find most characteristics to be important explanatory variables.

The research makes several important contributions as follows: First, the research uses a novel measure to accurately identify information sources in analyst reports. Previous studies (e.g., Ivkovic and Jegadeesh, 2004; Chen, Cheng, and Lo, 2010; Rubin and Segal, 2016) consider earnings release as the only public information announced by a firm. They argue that analyst reports written prior to an earnings announcement contain private information. Recent research (e.g., Huang, Lehavy, Zang, and Zheng, 2017) uses a topic modeling technique to extract the thematic content of texts. However, the sample of these studies is biased since they are likely to misclassify private information as public information. Even though a few studies read the reports per se for the classification, they either commit the same misclassification (Asquith, Mikhail, and Au. 2005) or obtain incomplete findings (Daniel, Lee, and Naveen, 2015).

To address the classification issue, the study applies an advanced textual analysis technique known as a regular expression for a pattern search on a headline of analyst reports. This algorithm allows the research to explain a possible market reaction channel of forecasts in terms of accuracy. Therefore, based on the better classification design, the research provides an answer to the question from Lo (2012) and further adds to a growing literature on analysts' roles as an information intermediary by providing evidence that information from private research efforts improves forecast accuracy which investors stronger react to.

More importantly, the study proposes a new explanation on the superiority of private information by showing that forecasts written based on it are more accurate and informative since analysts make more efforts for additional private information sources. This is different from analysts' information advantage hypothesis that previous literature argues based on their better position to access to private information sources.

Second, besides the consequences, the research extensively explores the determinants of the level of a private research effort by testing various characteristics of a firm as well as an analyst since previous literature (e.g. Daniel, Lee, and Naveen, 2015) identifies the limited number of the determinants of private efforts. Thus, the paper contributes to the literature by identifying more explanatory variables.

Third, with help from textual analysis, the study has by far the largest sample possible to examine the economic consequences and the determinants of private research efforts. The sizable sample also helps to generalize the findings to a larger analyst report universe.

This paper proceeds as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 explains the research design and the sample selection. Section 4 presents the main empirical analyses. Section 5 describes the robustness checks. Section 6 discusses the change analyses for the causality. Section 7 compares analyst effort vs. information advantage hypothesis. Section 8 illustrates the determinants of analysts' private research efforts. Section 9 concludes the paper.

2. Literature review and Hypotheses development

This section provides the relevant literature review on analysts' information sources and develops the hypotheses.

2.1 Literature on analysts' information sources

Based on the availability of a public information source, the literature (e.g., Ivkovic and Jegadeesh, 2004; Chen, Cheng, and Lo, 2010) identifies analysts' two roles as an information intermediary, where they provide value to investors; information discovery and interpretation role.[28] In other words, analysts *discover* information from sources not available to the public, whereas they *interpret* information from sources available to the public. Alternately, they obtain *private* information through private research efforts and *public* information by analyzing public disclosures.

[28] Huang, Lehavy, Zang, and Zheng (2017) argue that discovery represents analysts' private research efforts to produce new topics not readily available in the conference call, but the sources of the information include various public and private channels. Given that the research explores the information sources, it does not use the following terms: discovery and interpretation. Instead, the study uses private and public information sources. See footnote 3.

In light of this, recent research investigates the relative value of two information research efforts. However, its findings are not complete since it is difficult to distinguish between private and public information sources in analyst reports. Specifically, prior research (Ivkovic and Jegadeesh, 2004; Asquith, Mikhail, and Au, 2005; Chen, Cheng, and Lo, 2010; Livnet and Zhang, 2012; Rubin and Segal, 2016) uses the classification schemes based on an event date such as an earnings announcement. For example, Ivkovic and Jegadeesh (2004) argue that analyst reports include only public information if they are issued between week 1 and 6 relative to two days after the earnings release date. They show that analysts' earnings forecasts and recommendations are more valuable based on private information than public information. Similarly, Chen, Cheng, and Lo (2010) and Livnat and Zhang (2012) focus on earnings announcements as the only significant corporate public information, but their findings are opposite to each other. The former finds that private information is more valuable, whereas the latter shows that public information is. Following on Livnat and Zhang (2012), Rubin and Segal (2016) find the superiority of private information in terms of both forecast accuracy and informativeness. Based on item 2.02 (Results of Operations and Financial Condition) of 8-K filings, Rubin, Segal and Segal (2017) classify private source information if reports do not include the item labeled as unanticipated 8-Ks. They find the negative (positive) association between private information and forecast error (market reaction). However, the classification based on either an earnings release date or 8-K filings cannot correctly identify which information is because reports before the earnings release or after the 8-K release might contain public information.

In addition to an earnings announcement, Asquith, Mikhail, and Au (2005) identify 10 more publicly announced events by reading analyst reports, and find that by definition, analyst reports issued in a nine-day window (i.e., +/- 4 days) relative to the event dates contain only public information. This design, however, could result in the same misclassification since these reports might include private information that analysts collect from an information source not open to the public.

To address the classification issues above, recent studies take advantage of textual analysis in two different ways. Different from Asquith, Mikhail, and Au (2005), Daniel, Lee, and Naveen (2015) directly read analyst reports to distinguish whether corporate events are publicly announced or not. Specifically, they read each report and classify whether the report contains a private or public information source, or both. They further identify whether a private information source is from management or non-management: The management sources include personal meetings, site visits/tours, conference calls, and investor/analyst meetings with management. The non-management sources are surveys of customers, discussions with executives in the supply chain (or channel checks), and industry contacts. Meanwhile, they define public information source when the events such as an earnings announcement are publicly announced. However, their findings are incomplete because using only over 3,500 reports, they show that private information is more informative, but do not explain the channel.

More recently, topic models from computational linguistics gain popularity because they provide their users with an overview of themes being discussed in texts. Huang, Lehavy, Zang, and Zheng (2017) employ this topic modeling approach for a comparison of the underlying topics between analyst reports issued right after earnings conference calls and the calls themselves. They define private information when the reports do not contain the topics from the calls, and public information otherwise. They claim that both private and public information provide value to investors. However, they do not compare forecast accuracy between two sources, which is an important link to market reaction. As they agree, moreover, their research methodology has the same measurement error since their defined private information might be from a publicly available information source.

2.2 Hypotheses development

Prior literature finds mixed evidence on the relative importance of private information versus public information sources. Moreover, some previous studies do not investigate a major channel (i.e., forecast accuracy) through which information sources affect investors' behavior. Even if they do, their findings might not be justified possibly due to the limitations in the identification schemes described above.

To overcome the identification shortcomings, Daniel, Lee, and Naveen (2015) differentiate between a private and public information source by reading a small size of analyst reports. In contrast, to design more sophisticated classifications with a greater sample size than theirs, the study employs textual analysis known as a regular expression for a pattern search on a headline of analyst reports. This algorithm allows the research to identify information sources with higher accuracy with more samples and thus, to explain a possible market reaction channel which they cannot provide.

It is obvious that accurate forecasts are highly demanded by investors for their investment decisions. To respond to this, analysts make more efforts to collect better information from various sources. Contrarily to public information, private information needs more resources such as time and money since analysts easily cannot access to the sources for the information with an insignificant cost. In spite of a higher information cost, analysts make such efforts to better understand the firm they cover, generating better forecasts in terms of accuracy (e.g., Rubin and

Segal, 2016; Rubin, Segal and Segal, 2017). They consistently find a higher accuracy of forecasts made based on private information sources.

Nevertheless, public information might generate as many accurate forecasts as private information. In other words, public information sources also can be useful for analyst performance. Thus, to have less error in forecasts based on private information, analysts exert *more* efforts to access more sources not available to the public (i.e., analyst effort hypothesis). Compared to forecasts based on a public information source, such *additional* private information source allows them to write more accurate forecasts. Accordingly, the first hypothesis is as follows:

Hypothesis 1: Additional private research efforts are positively (negatively) associated with earnings forecasts accuracy (error).

As discusses earlier, previous literature provides mixed evidence on the value relevance of private sources relative to public sources. However, suggested by the effort hypothesis above, forecasts with more accuracy through private research efforts tend to be more informative and value relevant.

Specifically, Loh and Mian (2006) document that analysts with superior forecast accuracy also issue more informative stock recommendations. Brown, Call, and Clement (2015) find that writing accurate forecasts is analysts' prior motivation, and analysts use such forecasts as inputs into their corresponding stock recommendations. To the extent that analysts with higher private research efforts issue more accurate forecasts, I expect a stronger market reaction to stock recommendations issued by such analysts.

Hypothesis 2: Additional private research efforts are positively associated with market reaction.

3. Research methodology and sample selection

3.1 Measurement of independent variable: analysts' private research effort level

The research question of interest is how analysts gather/process information for their reports, particularly, the more private research efforts they make, the better forecast and stronger market reaction. The level of private research efforts is measured by the number of information sources not available to the public that analysts utilize to make earnings forecasts in the reports. Accordingly, private and public information sources need to be defined first.

Referring to recent research (Daniel, Lee, and Naveen, 2015), I define two sources of information in analyst reports depending on its public availability, i.e., private (or proprietary) and public information sources. Specifically, analysts collect private information from non-publicly available sources such as a personal meeting with management (*meeting*), site visit/tour (*tour*), conference call (*call*), investor/analyst day (*invtday*), customer survey (*survey*), supply chain check (*channel*), and industry conference (*conference*). Broadly, the first four are from management (*mgt*), whereas the last three are not engaged with management (*nonmgt*), but from supply chains or industry contacts. More specifically, seven information source variables above are a dummy variable, for instance, *meeting* equal to 1 when analysts describe a meeting with management in person in their reports. However, since a conference call might be either open or closed to the public (Bushee, Matsumoto, and Miller, 2003). I separately test sample excluding it from private information sources.[29] Appendix A defines the variables of information sources whose examples from analysts' research reports are shown in Appendix B with words in bold as a part of regular expression.

[29] The results do not change. Huang, Lehavy, Zang, and Zheng (2017) classify a conference call as a public information source.

On the other hand, analysts gain public information from sources open to the public, i.e., firms' event announcements mainly through U.S. Securities and Exchange Commission (SEC) filings or news media, which is an intercept in a regression model below. They process public information by interpreting it for their report users to clearly understand. Three public information sources are defined as follows: *ea* is equal to 1 if the information source is post-earnings announcements, *preea* equal to 1 if it is pre-earnings announcements, *nonea* equal to 1 if it is any public information other than earnings announcements and 0 otherwise.

Compared to public sources, analysts make more efforts to access to private information process by spending more resources such as time and money. Accordingly, I define two main independent variables if analysts use one (*private1*) or two (*private2*) private information sources for the reports, which I predict affects their forecast accuracy and investors' reaction.

3.2 Measurement of dependent variables: earnings forecast accuracy and market reaction

The first main dependent variable is forecast accuracy that analysts have in their reports. Based on Hong and Kubik (2003), forecast accuracy in percentage is measured as follows:

$$afe_{i,j,t} = 100 \text{ x } |forecast_{i,j,t} - actual_{j,t}|/price_{j,t} \qquad (1)$$

where $afe_{i,j,t}$ is the absolute forecast error for analyst $_i$, following firm j in year t, $forecast_{i,j,t}$ is the last one-year-ahead forecast of annual earnings of firm j for fiscal year t issued by analyst i, $actual_{j,t}$ is the actual annual earnings for firm j in year t, and $price_{j,t}$ is the latest monthly stock price from Compustat of firm j in fiscal year t. Earnings forecasts are from Investext while actual earnings from I/B/E/S. The higher absolute forecast error, the lower forecast accuracy.

Analysts make a positive (or upward) or negative (or downward) forecast error. The question is which error is more reduced by analysts' private research efforts. Accordingly, the absolute value of a positive forecast error (*afeup*) is defined as the absolute value of earnings forecast error when earnings forecast is greater than actual earnings, whereas that of a negative forecast error (*afedown*) is opposite.

To test the informativeness of the reports issued by analysts with more private research efforts, the second main independent variable, i.e., cumulative abnormal return (*car*), is measured as the sum of daily market-adjusted abnormal return during three ([-1, +1]) (or seven ([-1, +5])) days starting from one day before an analyst earnings forecast date as day 0. Analyst forecast dates are captured from the reports per se downloaded from Investext. The daily stock return is based on the holding period return from CRSP, and the market return is the daily value-weighted return including all distributions of U.S. stocks from CRSP.

3.3 Regression specification

I separately regress dependent variables of analysts' earnings forecast error and investors' reaction on analysts' private research effort levels. The multiple linear regression model below has three levels of private information sources which are coded as a categorical variable rather than a continuous one, for which all the information concerning three levels is accounted for. Again, private information that analysts discover for the forecasts through one of channels such as *meeting*, *tour*, *call*, *invtday*, *survey*, *channel*, and *conference* is the variable of interest. Thus, I create *private0* whose value is equal to 1 if analyst reports have no private but public information, and 0 otherwise. *private1* has a value equal to 1 if the reports have a single private information source, and 0 otherwise. Likewise, *private2* is created for the reports with two private information sources. To test the additional effect of *private1* and *private2*, *privatet0* is included as an intercept in the model. I also control for various factors that might affect analysts' forecast accuracy and stock market, including a year fixed effect to control for common time trends, and an industry (a bank) fixed effect to account for cross-industry (bank) differences. Baseline regression model is as follows:

$$dependent=\beta_0 + \beta_1 private1 + \beta_2 private2 + \beta_3 \Sigma analyst + \beta_4 \Sigma firm + \beta_5 industry\ F.E. + \beta_6 bank\ F.E. + \beta_7 year\ F.E. + \varepsilon \qquad (2)$$

where the dependent variables (*dependent*) are the proxies for either absolute forecast error (*afe*) in year *t* in a forecast error model or cumulative abnormal returns (*car3* and *car7*) in year *t* in a market reaction model. All the independent variables are measured in year *t-1* or year *t*. The key variables of interest (*private1* and *private2*) are the proxies for analysts' private research effort levels measured as the number of the information sources (i.e., *meeting*, *tour*, *call*, *invtday*, *survey*, *channel*, and *conference*) from which they privately discover information. The rest of variables control for factors which influence dependent variables. Standard errors are cluster-adjusted at firm and by year levels. Appendix A provides variable definitions.

I follow the previous literature to control for two sets (Σ*analyst* and Σ*firm*) of characteristics that affect how accurately analysts make forecasts and how strongly investors react to the forecasts, i.e., analyst and firm characteristics. According to prior research (e.g., Clement, 1999; Rubin, Segal, and Segal, 2017), analyst characteristics can explain analyst performance such as forecast accuracy. Thus, I control for the following analyst-specific variables in both forecast accuracy and market reaction models: analyst's experience following the firm (*firmexp*) and the industry (*industryexp*) measured as the number of years the analyst covers the firm and the industry as of year t, respectively; analyst's busyness calculated as the number of firms (*firm_covered*) and industries (*industry_covered*) covered by the analyst in year t, respectively; resources of the brokerage house (*brsize*) defined as the number of analysts employed by the brokerage firm employing the analyst in year t. Clement (1999) finds that closer forecasts to earnings announcements are more accurate. Similarly, I control for forecast uncertainty (*horizon*) calculated as the number of days from the forecast date to fiscal year-end since a longer time period between the dates increases forecast error (Richardson, Teoh, and Wysocki, 2004). In a market reaction model, I additionally control for the levels (*buy* and *sell*) and change (Δ*recom*) of analyst recommendations and forecast accuracy (*afe*).

Then, I control for variables as a proxy for the firm's financial and operating risk, and information environment. These firm-specific variables are included in both forecast accuracy and market reaction models. Specifically, I control for the growth opportunities of a firm such as its size (*logmv*) measured as the natural logarithm of its market value of equity at year-end and its market value (*mb*) calculated as a market value divided by a book value at year-end, its profitability (*roa*) in terms of a ratio of income before extraordinary items to total assets at the end of year *t*, its leverage (*leverage*) defined as total liabilities scaled by total assets at the end of year *t,* and its previous return volatility (*retstd12*) measured as the standard deviation of its daily stock return during 12 months prior to an analyst forecast date.

Finally, I also control for a firm's information environment by including an indicator variable (*loss*) equal to 1 if it has negative earnings during three fiscal years before an analyst forecast, and 0 otherwise, the number of analyst following (*lognanalyst*) calculated as the natural logarithm of the number of analysts following the firm in the previous year, and institutional investors' holding (*iholding*) defined as the total number of shares held by institutions divided by shares outstanding at the end of the same quarter.[30] All continuous variables are winsorized at 1 and 99 percentiles to reduce the effect of outliers.

3.4. Sample selection

[30] The percentage holdings of institutional investors are zero if no institutional investors report positive holdings for a firm-quarter.

To test the relative value of private and public information sources, analysts' information sources are first identified by reading the reports from 10 global investment banks downloaded from Investext. Using a regular expression, a sequence of characters that define a search pattern, I detect analyst reports including the headlines which describe information sources such as management meetings with management, site visits/tours, conference calls, investor/analyst days, customer surveys, supply chain checks, industry conferences, post-earnings announcements, pre-earnings announcements, and non-earnings announcements.[31] The first seven are classified as private information sources while the rest three are public information sources. Then, I drop the reports which have both private and public information sources from the sample to ensure a clear comparison.

The identification accuracy on the headlines of analyst reports is more than 95% because similar with news headlines, the report headlines are succinct but more importantly, contain enough words relevant to information sources, which is appropriate for a sophisticated regular expression.[32]

For instance, the regular expression (/(?<!meeting)(host(ed)?(?! investor)(?! bus)|me(e)?t (with)?|(?<!investor)meet(ing|ings)?(with)?)\s(\S+\s){0,3}(chairman|management(?!investor)|mgmt|ceo|cfo|coo|executives?|directors?|vp|head|president|sales|ir\b)/) correctly detects all examples of personal meetings with management in Appendix B.

In contrast, the first (i.e., cover) page is not considered because it might contain both a main event with discussion and an upcoming relevant event without it, e.g., both discussion on earnings results and a schedule of an analyst meeting.

[31] The research widely extends the classification designed by Daniel, Lee, and Naveen (2015),

[32] The first 50 words of analyst reports are also used to identify information channels. The size of final sample increases up to 200,729 reports with about 75 % of identification accuracy. The regression results in the study are similar with those from the first 50 word sample.

Then, information source data merges analyst data from I/B/E/S, financial data from Compustat, and stock price data from CRSP. Appendix C shows that 10 banks issue 81,762 reports for 10,887 U.S. firms followed by 2,030 analysts during 2000-2014. The final sample contains 81,762 observations from 10 unique banks for 15 years, 1,903 unique analysts, 3,612 unique firms, and 25 industries.

4. Empirical results

4.1 Descriptive statistics

Table 1, Panel A, provides the descriptive statistics for main variables. In the sample, the mean values of *private1* and *private2* are 0.148 and 0.003, meaning that about 15% of the sample uses one private information source while only 0.3% includes two. This implies that analysts tend to make less effort to dig out proprietary information compared to the effort on public information. As for forecast accuracy, the mean values of *afe*, *afeup*, and *afedown* are 1.438, 2.745, and 0.862, respectively. This suggests that analysts are more likely to make an error on their forecasts, specifically, a positive error due to the higher mean value of *afeup* than *afedown*. Meanwhile, the market shows a negative reaction to analyst forecasts with -1.581% and -2.709% of the mean values of each cumulative abnormal return (*car3* and *car7*). Consistent with previous literature, analysts tend to issue more buy recommendations than sell ones since their mean values are 0.536 and 0.063, respectively.

Panel B of Table 1 reports the summary statistics by information sources. Information from management (*mgt*) consists of 14% of the sample measured as the sum of *meeting*, *tour*, *call*, and *invtday*, whereas information from non-management (*nonmgt*) accounts for 1.4% calculated as the sum of *survey*, *channel*, and *conference*. Based on these two sources, *private1* and *private2* are constructed. Specifically, to ferret out private information, analysts are more likely to attend an investor/analyst day with the mean value of 0.082 (i.e., 8.2% of the sample) followed by a personal meeting with management (0.028), conference call (0.023), and site tour (0.007). On the other hand, 78% of the report sample describes earnings announcement (*ea*) publicly made by a firm, suggesting what most high-paid analysts do, i.e., processing public information. The overall average value of all information sources is 1.185 (i.e., 119% of the sample) since some of them are duplicated.

Panel A of Table 2 shows the sample distribution by year during 2000-2014.[33] Over the years, analysts generally use more private information sources for forecasts, whereas forecast error gradually decreases. This increases the informativeness of such forecasts, resulting in a stronger market reaction to them. Specifically, the mean value of absolute forecast error (*afe*) increases during two financial crisis periods (i.e., 2001, and 2007-2009).[34] Following the crises when they tend to conservative to incorporate new information, analysts make more efforts by collecting/using more private information for forecasts, resulting in less *afe* compared to 1.473 of its mean value. This suggests that research efforts to discover private information are likely to reduce forecast error.

Panel B of Table 2 summarizes the distribution of the sample by 24 industry groups in terms of the Global Industry Classification Standard (GICS) codes. Based on the sum of *private1* and *private2*, Pharmaceuticals, Biotechnology & Life Sciences, Insurance, and Technology Hardware & Equipment are top three industries which analysts collect information through private channels rather than depend on a firm's public information. These industries tend to hold more investor/analyst days and industry conferences. Meanwhile, Banks has the highest forecast

[33] The sample period starts on January 18, 2000 and ends on November 12, 2014. Thus, there are fewer observations in both 2000 and 2014.
[34] The National Bureau of Economic Research (NBER) reports that the recession periods are from March 15th, 2001 to November 15th, 2001, and from December 15th, 2007 to June 15th, 2009.

error with 2.735 of its mean value, followed by Real Estate with 2.643 and Telecommunication Services with 2.623. Since they are likely to have more intangible assets, it is more difficult for analysts to make accurate forecasts. Graphically, Panel B of Table 2 shows that the number of private information sources is negatively related to the level of forecast error, but positively associated with the market reaction. This hints that forecasts with private information sources prone to have a fewer forecast error which investors value.

Table 3 displays the Pearson correlation matrix. As expected, the levels of private information sources (*private1* and *private2*) are significantly and negatively correlated with forecast error (*afe*), but positively correlated with the level measures of market reaction (*car3* and *car7*). This suggests that the more private research efforts, the better forecast accuracy and the stronger market reaction. As expected, the level measures of market reaction (*car3* and *car7*) and *afe* are significantly and negatively correlated. Both *private1* and *private2* are significantly and positively related to the size of analysts' employer (*brsize*) and covering firm (*logmv*) where analysts can access to more private information channels. On the other hand, *private1* and *private2* are negatively related to the measures of an analyst's busyness (*firm_covered* and *industry_covered*). This implies that when analysts are busier with more firms and industries to cover, they tend to count on more public information sources and thus make fewer efforts to find private information sources.

Table 4, Panel A, shows how the sample is distributed by the levels of private information sources. As in the descriptive statistics, *private1* and *private2* account for 15.13% combined. Panel B of Table 4 summarizes that analysts overwhelmingly secure 1 private information (*private1*) through management sources (*mgt*) among which investor/analyst day (*invstday*) accounts for over 50%, followed by a personal meeting with management (*meeting*) and a conference call (*call*). As for non-management sources (*nonmgt*), an industry contact such as an industry conference (*conference*) is the number one source for private information. When it comes to *private2*, analysts use two sources from management to discover proprietary information over 61% of the time. Panel C of Table 4 explains the two sources in detail of which 40% (96/241*100) consists of the combination of a personal management meeting and an investor/analyst day.

4.2 Univariate test

Table 5, Panel A, displays the mean comparisons by private research effort levels. As the effort level increases, the forecast error (*afe*) significantly decreases, suggesting initial evidence that the more private information sources, the higher forecast accuracy. Accordingly, market reaction also becomes stronger, especially, significantly from non-private information (*private0*) to one (*private1*). Panel B of Table 5 shows that when analysts take advantage of single private information (*private1*) to make forecasts, management sources are more useful to reduce forecast error (*afe*).

Given that there is one more proprietary information to use (*private2*), more accurate and informative forecasts can be made by the combination of management and non-management sources compared to that of management sources themselves. Overall, the univariate comparison suggests that more private research efforts improve forecast quality in terms of its accuracy and thus drives a stronger market reaction.

4.3 Main regression analyses

All previous analyses indicate that the number of private information sources has a negative (positive) relationship with the level of forecast error (market reaction). In this section, I investigate the multiple regression model specified in Section 3 with/without control variables.

4.3.1 Analysts' private research effort and earnings forecast accuracy

Table 6 reports the linear regression results of the effect of the number of private information sources on analysts' earnings forecast error. First, coefficients on *private1* are not significant across the models since a single public information source influences forecast error as much as a single private source does, implying that public sources are also useful for analyst performance. In Columns (1) and (2), however, *private2* is significantly and negatively related to *afe*, suggesting that forecasts made with additional private information source are less (more) likely to have forecast error (accuracy). The statistical significance of its coefficient is stronger even with control variables than without. This is consistent with the first hypothesis.

Then, the question is which forecast error a private information source can reduce, i.e., positive or negative forecast error. Columns (3) to (6) have the answer, showing that proprietary information is more likely to decrease positive forecast error (*afeup*) than its counterpart (*afedown*), especially with control variables.

The results show that all coefficients on *private2* but those in the negative forecast models are negative and significant at $p<0.01$ while that of *private1* is not. More importantly, the results indicate the economic impact of an additional private information source. For instance, the model 2 of Table 6 finds that the magnitude of *private2* is large (i.e., -0.488 of its coefficient), meaning that additional private information reduces forecast error (*afe*) by almost a half dollar. Alternatively, a one standard deviation increase in *private2* is associated with a decrease of 0.03 in *afe*. This effect is economically significant as it represents a 2.1% decrease below the mean *afe* of 1.438. This also leads to a 1% standard deviation reduction in *afe*, all else equal. The results suggest that the negative association between private information and forecast error is statistically and economically significant. Overall, Table 6 confirms the prediction that extra information from private sources increases (reduces) forecast accuracy (error).

Meanwhile, all firm-specific variables except for the number of analyst following (*lognanalyst*) are statistically significant at the 1% level across the models. Specifically, forecast error (*afe*) is negatively related with a size (*logmv*), market value (*mb*), profitability (*roa*) and institutional investor's holding (*iholding*) of a firm, but positively related to its risk such as previous return volatility (*retstd12*) and negative earnings experience (*loss*). On the other hand, all analyst-specific variables are not significant except for *horizon* which is positively related to *afe*, suggesting that with a longer horizon (i.e., more days to fiscal year-end from a forecast date), analysts tend to have more forecast errors since they have less accurate information and thus make more assumptions on the forecasts.

4.3.2 Analysts' private research effort and market reaction to stock recommendations

In order to determine the usefulness of private information sources, I analyze their information content. Given that analysts issue more accurate forecasts using private information sources, I expect a stronger market reaction to stock recommendations issued by them. To test the relative importance of information sources on market reaction to recommendations, I estimate the market reaction model in Equation 2. Specifically, I regress *car3* (or *car7*) on the levels of private sources (*private1* and *private2*), controlling for the characteristics of recommendations (*buy*, *sell*, and Δ*recom*), forecast error (*afe*) and all variables from specifications of Table 6.

Table 7 shows that across the models, all proxies (*private1* and *private2*) for the number of private information sources are significantly and positively related to those (*car3* and *car7*) for cumulative abnormal return. Specifically, all coefficients on private1 are positive and significant at p<0.01. All coefficients on *private2* except for that in Column (1) are at p<0.05, suggesting their statistical significance. However, the magnitude of *private2* is almost twice greater than *private1* because all coefficients on the former are bigger than those on the latter across the models, suggesting that market reaction is higher for stock recommendations issued by analysts with higher private research efforts. In other words, one unit increase in *private2* (i.e., an increase of additional two private information) will increase cumulative abnormal returns by 1%. More specifically, in Column (2), a one standard deviation increase in *private2* increases a standard deviation in *car3* by 1% compared to that in *private1* by 0.26%. Overall, the results suggest that in addition to its statistical significance, private information source have an economic impact on stock returns if I fix all the other variables at a fixed value, implying that investors value the hard work analysts make for forecasts, and recognize their accuracy and informativeness.[35]

Consistent with previous literature on analysts' signals, cumulative abnormal returns (*car3* and *car7*) are positively associated with both a buy recommendation (*buy*) and its change *(*Δ*recom*), whereas negatively with a sell recommendation (*sell*). As for control variables specific to analysts, they also have a positive relationship with brokerage size (*brsize*), industry experience (*industryexp*), and the number of days from a forecast date to fiscal year-end (*horizon*). On the other hand, they are negatively correlated with forecast error (*afe*), and firm experience (*firmexp*). In terms of firm-specific control variables, cumulative abnormal returns are negatively related with a firm's size (*logmv*), leverage (*leverage*), past return volatility

[35] I run separate regressions on buy and sell recommendations due to asymmetric market reaction after controlling for the change of recommendations along with all variables form Table 6. The untabulated reports show the similar results with those of Table 7.

(*retstd12*), and the number of analyst following (*lognanalyst*). Only the market value (*mb*) of a firm is positively associated with cumulative abnormal returns.

4.3.3 Analysts' earnings forecast accuracy and market reaction based on the type of private information sources

In the descriptive statistics section, Panel C of Table 4 displays the distribution of the level of private research efforts equal to 2 (*private2*) based on two main information sources, i.e., management (*mgt*) and non-management (*nonmgt*) sources. In the main regression analysis section, Table 6 and 7 show the negative effect of *private2* on forecast error (*afe*) and its positive consequence on market reaction (*car3* and *car7*), respectively. In this section, I investigate the impact of *private2* in terms of two information sources in both the forecast error model and the market reaction model since *private1* is not significant in the first model.

Table 8, Panel A, includes two variables for two private information (*private2*), i.e., *private2single* (*private2mix*) equal to 1 if analysts collect information from two (at least one) management (non-management) sources, and 0 otherwise. In Panel C of Table 4, there are two types of the combination for *private2mix*, i.e., one from one management and one non-management source (e.g., an investor/analyst day and an industry conference) and another from two non-management sources (e.g., a channel check and an industry conference). Table 8 does not include the latter since there is only one combination of two non-management sources. Specifically, Panel A of Table 8 shows that all the coefficients on *private2mix* are negative and significant at the 1% level except for that in model 3 at the 5% level. This implies that forecasts made based on two private information for which analysts acquire from both one management source and one non-management source are more likely to have the least errors across the source types. This also suggests that private information from a supply chain analysis (*channel*) or an industry meeting (*conference*) is as useful as management-source information for analysts to produce more accurate forecasts since the information contains a big picture of the firm analysts follow, which helps them better understand the firm. Meanwhile, the association between *afe* and control variables is similar to that in Table 6.

Panel B of Table 8 reports that almost all types of source variables except for *private2single* are positive and significant at $p<0.01$. This indicates that private information is informative for investors to make their investment decisions. Especially, additional proprietary information from each of management and non-management sources contributes to higher cumulative abnormal returns (*car3* and *car7*) since the coefficients on *private2mix* are bigger than any other ones. As for control variables, their signs are similar to those in Table 7.

Collectively, private information from both management and non-management sources is useful for analysts because they are able to make more accurate forecasts. Such information is also beneficial for investors to make a better judgement on their investment.

5. Robustness checks

In this section, I implement a battery of robustness tests on the results of Table 6 and 7. The results are robust to different specifications using a different measure of forecast errors as well as more control variables, and to the mean value regression of forecast errors.

5.1 Additional control variables (i.e., Form 10-K readability and analyst connection), and a new forecast error measure

First, I replicate the results of Table 6 and 7 using the readability level of annual reports (i.e., Form 10-Ks) (*readability*) and analysts' relationship with the covered firm (*connection*) as additional control variables which may affect forecast accuracy and market reaction. Specifically, referring to previous research (De Franco, Hope, Vyas, and Zhou, 2015), I first create a measure of readability levels of 10-Ks (*readability*) defined as aggregate readability measure of Gunning-Fog Unreadability Index, Kincaid Flesch-Kincaid Grade Level index, Flesch Reading Ease Score, and Smog Readability Index by multiplying the first two and the last one by negative one to ensure that all components are increasing in readability, ranking each component into percentiles from 1 to 100, and then taking the average across the four components.[36] Interpretation of the 10-K readability measure is that the higher readability, the easier it is to read.

On the other hand, analysts may have various relationships with the firm they follow, i.e., a client, investment banking, and/or brokerage; they even can own a share of the firm. These connections with the covered firm might influence analysts' ability on forecasts and thus the informativeness of forecasts. Accordingly, I create a variable named *connection* equal to 1 when analysts have any types of these relationships with the covered firm, and 0 otherwise.

Instead of forecast error divided by average monthly stock price in equation 1, I use actual earnings as a scaler, create a variable named *afeact*, and include in Columns (2), (5), and (6) of Table 9 for comparison with Columns (1), (3), and (4) of Table 9.

Consistent with the results of Table 6 and 7, *private2* is significantly negatively related with both *afe* and *afeact*, and has a significantly positive association with *car3* and *car7*. This suggests that more private information sources improve analyst performance in terms of forecast accuracy and thus, strengthen investors' belief in the forecast. The directions of the control variable are similar to those in Table 6 and 7.

[36] Fog index refers to Gunning-Fog Unreadability Index, calculated as -1 x ((0.4 x words per sentence) + (100 x complex words per word)). Kincaid Flesch-Kincaid Grade Level index is calculated as -1 x ((0.39 x words per sentence) + (11.8 x syllables per word) – 15.59)). Flesch Reading Ease Score is measured as 206.835 – (1.015 x words per sentence) – (84.6 x syllables per word). Smog Readability Index is calculated as -1 * (1.043 x sqrt (# complex words x 30/# sentences) + 3.1291).

5.2 Mean value regressions of earnings forecast error

To eliminate the undesirable effect from extreme values of variables, I repeat the models in Table 6 using the mean values of all variables except for private information source variables. This process reduces the number of observations to slightly more than 1,700 on average. Table 11 shows the results with a bank fixed effect included and standard errors cluster-adjusted at a bank level. Consistent with the findings of Table 6, more private research efforts (*private2*) significantly decrease average forecast errors across the models.

Meanwhile, the untabulated results of mean value regressions show that market reaction is consistent with that of Table 7.

6. Change analyses

So far, the findings show the robust association of private information with forecast accuracy and market reaction. Next, based on the panel data, I can implement time-series tests to find a possible causal relationship by investigating a directional impact; and to eliminate a fixed effect. Specifically, causality may be established by dealing with reverse causality by self-selection since analysts making forecasts with more errors are more likely to exert more private research efforts. To address this endogeneity issue, I conduct a change analysis on both forecast error and market reaction models. Specifically, I examine whether an increase in the number of private information sources (*privateincrease*) in analyst forecasts are negatively associated with changes in forecast error (*afechg*) and positively related to changes in cumulative abnormal returns (*car3chg* and *car7chg*). Table 9 shows the results. In Columns (1) and (2) of Table 10, increase in proprietary information sources (*privateincrease*) is significantly negatively related to change in forecast error (*afechg*) at $p<0.01$, consistent with the findings for the level of private information sources in Table 6 and 9.

I further examine the change in market reaction in Columns (3) to (6) of Table 10. Coefficients on an increase in input levels are positive and significant at the 1% level, suggesting the informativeness of additional private information, in line with the results in Table 7 and 9.

In general, the results of the change analyses imply that more proprietary information from a private source may *cause* decrease in forecast errors and increase in market reaction.

7. Analysts' private research effort vs. information advantage

I find that analysts with more private research efforts tend to make superior forecasts. In other words, forecasts by these analysts have better quality in terms of accuracy which investors favorably react to. However, according to an analyst black box survey paper (Brown, Call, and Clement, 2015), analysts, especially, those who work at big brokerage firms, are more likely to make better forecasts because of information advantage from private phone calls with management. Therefore, it is crucial to investigate whether analysts' private research efforts also produce better forecasts.

For this task, I construct a sample by identifying analysts who do not make any effort on private information sources in the first place, but make efforts afterward. Specifically, if forecasts from these analysts with high efforts (*high_type*) have less error and a stronger market reaction, then the research is consistent with analyst effort hypothesis. Otherwise, it is based on analyst information advantage explanation. *high_type* is an indicator variable equal to 1 if private research efforts are greater than 0 after no effort in the first place.

Columns (1) and (2) of Table 12 show that *high_type* and *afe* are negatively related at $p<0.05$, suggesting that generally, high efforts on additional private information is instrumental for analysts to make more accurate forecasts. Based on a comparison of Columns (3) and (4) with Columns (5) and (6), high effort analysts are less likely to make negative forecasts than positive ones. Control variables have a similar pattern with that in Table 6.

Consequently, the results of Table 12 support the effort hypothesis in Section 2, providing a new perspective on analyst performance, especially, in terms of forecast accuracy.

Meanwhile, market reaction is also investigated, and its untabulated results show a similar pattern with the market reaction of Table 7.

8. Determinants of analysts' private research efforts

To identify the determinants of the level of proprietary information (*private*) analysts discover from private sources, I regress a categorical variable, *private*, on analyst and firm characteristics using ordered logit regression. The specification includes all independent variables of Panel A of Table 9. In addition, I add more analyst-specific variables: analyst gender (*female*) equal to 1 if the analyst is a female, and 0 otherwise; analyst location (*foreign*) equal to 1 if analyst resides outside of U.S., and 0 otherwise; analyst education level (*graduate*) equal to 1 if analyst holds a graduate degree, and 0 otherwise. I also create one more firm-specific variable, *turnover*, calculated as 100 times the number of shares traded for a firm deflated by the total number of common shares outstanding in year *t*. Model 1 and 2 of Table 13 do not include any fixed effect without any clustering, whereas Model 3 and 4 contain all three fixed effects with firm clustering.

The results of Table 13 show that analysts from a large brokerage house (*brsize*), with more days to fiscal year-end from forecast date (*horizon*), with a graduate degree (*graduate*), or with more connections with the firm they follow (*connection*) are more likely to make more efforts to dig out private sources for more proprietary information. On the contrary, analysts with more firms to cover (*firm_covered*) or those residing in non-U.S. countries (*foreign*) tend to exert less private research effort because they are busy or have fewer information sources outside of the U.S..

Table 13 also finds that analysts following a firm in a bigger size (*logmv*), with higher standard deviation in previous returns (*retstd12*), or with more percentage of institutional investors (*iholding*) are more likely to be more efforts to secure more private information. On the other hand, analysts covering a firm with higher profitably (*roa*) or less readable 10-Ks (*readability*) are less likely to make an effort on the detective work to find private information sources.

9. Conclusion and Future Direction

There is a little literature on what analysts do, that is, how they produce their research reports. Put differently, we know little about what information source analysts use to make forecasts, and which information source is more valuable. As an information intermediary, analysts access to *private* and/or *public* information source of a firm to make forecasts for investors. Previous studies consistently find a higher accuracy of forecasts made based on private information sources. Two sources, however, might equally useful for analysts to reduce forecast error. In terms of value relevance, prior research finds mixed evidence. This is because prior studies cannot precisely identify private and public information sources.

To address the identification issue, the research implements advanced textual analysis using a regular expression for a pattern search on a headline of 81,762 analyst reports during 2000-2014. The study finds that there is no significant difference between single private and single public information source in terms of analysts' earnings forecast error (or accuracy), but an additional proprietary information source might *cause* a decrease (increase) in forecast errors (accuracy). Given that an additional private source requires more efforts to get on the part of analysts (even when they do not have an information advantage), investors highly appreciate the efforts by reacting stronger to a recommendation issued based on forecasts containing the private information. This new perspective makes the study to be differentiated from previous literature supporting analysts' information advantage hypothesis.

Further analysis shows that the combination of two private information from each of management and non-management sources is more likely to reduce more forecast errors and to stronger market reaction than any other combination. Additional cross-sectional analyses investigate the determinants of the level of private information sources based on a variety of analyst and firm characteristics, and find most of them to be significant explanatory variables.

The most significant contribution the research makes to the literature is developing a novel measure to accurately identify information sources in analyst reports which previous studies cannot. Specifically, the study employs advanced textual analysis known as a regular expression for a pattern search on a headline of analyst reports. This algorithm allows the research to explain a possible market reaction channel, i.e., forecast accuracy.

Institutional Investor (II) magazine selects the best research analysts every year. [37] However, it is a reasonable concern that their methodology might be highly subjective because the weighting of votes is heavily skewed toward institutions with the most assets under management and those that pay Wall Street the most commissions and thus, selected analysts have an information advantage. Using a sample of the best analysts of the year from the magazine, future research investigates whether these All-Star analysts make as much effort to discover private information sources to live up to their reputation and compensation. If this is

[37] The All-America team is selected by a survey of research directors and chief investment officers of major asset management firms, including the largest U.S. money managers and significant U.S., European and Asian institutional investors. Clients get into the mix and analysts themselves are asked to assess their peers. See the link (https://www.institutionalinvestor.com/research/7394/Methodology) for more detail.

empirically true, then they deserve to be a star since they work hard rather than have information advantage in access to proprietary sources.

It is important to note that my results might be subject to limitations. For example, while I conduct textual analysis based on headlines and the first 50 words of analyst reports, I acknowledge that such a decision can potentially lead to the issue of an incomplete sample. To reduce this concern, I validate the accuracy of the keyword identification by applying the textual analysis to 20 randomly selected analyst reports with full length. My result indicated that although I am able to identify more matches using the entire report instead of focusing on only the headline and top 50 words, the correlation of the keywords identified using my current approach and the full report is close to 70%. This finding suggests that although the accuracy of keyword identification can indeed increase using the full report, the focus on the headline and first 50 words can represent a reasonable tradeoff between effort and efficiency given the large number of analyst reports.

References

Asquith, P., Mikhail, M., and Au, A., 2005. Information content of equity analyst reports. Journal of Financial Economics 75, 245-282.

Beyer A., Cohen D., Lys T., and Walther B., 2010. The financial reporting environment: Review of the recent literature. Journal of Accounting and Economics 50, 296–343.

Bradshaw M., 2011. Analysts' forecasts: What do we know after decades of work? Working paper, Boston College, Chestnut Hill, MA.

Brown, L., Call, A., and Clement, M., 2015. Inside the "Black Box" of Sell-Side Financial Analysts. Journal of Accounting Research 53, 1–47.

Bushee, B., Matsumoto, D., Miller, G., 2003. Open versus closed conference calls: the determinants and effects of broadening access to disclosure. Journal of Accounting and Economics 34, 149–180.

Chen, X., Cheng, Q., and Lo, K., 2010. On the relationship between analyst reports and corporate disclosures: Exploring the roles of information discovery and interpretation. Journal of Accounting and Economics 49, 206–226.

Clement, M., 1999. Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter?. Journal of Accounting and Economics 27, 285–303.

Daniel, N., Lee, S., and Naveen, L., 2015. Information discovery by analysts. Working paper.

De Franco, G., Hope, O.K., Vyas, D., and Zhou, Y. 2015. Analyst report readability. Contemporary Accounting Research 32, 76–104.

Hong, H., and Kubik, J. D., 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. The Journal of Finance 58, 313–51.

Huang, A., Lehavy, R., Zang, A., and Zheng, R., 2017. Analyst Information Discovery and Interpretation Roles: A Topic Modeling Approach. Management science 63, 1–23

Ivkovic, Z. and Jegadeesh, N., 2004. The timing and value of forecast and recommendation revisions. Journal of Financial Economics 73, 433-463.

Livnat, J., and Zhang, Y., 2012. Information interpretation or information discovery: Which role of analysts do investors value more?. Review of Accounting Studies 17, 612-641.

Lo, K., 2012. What do analysts do? Discussion of "Information interpretation or information discovery: which role of analysts do investors value more?". Review of Accounting Studies 17, 642-648.

Loh, R. and Mian, G., 2006. Do accurate earnings forecasts facilitate superior investment recommendations? Journal of Financial Economics 80, 455-483.

Ramnath, S., Rock, S., and Shane, P., 2008. The financial analyst forecast literature: A taxonomy with suggestions for future research. International Journal of Forecasting 24, 34–75.

Richardson, S., Teoh, S., and Wysocki, P., 2004. The Walk-down to Beatable Analyst Forecasts: The Role of Equity Issuance and Insider Trading Incentives. Contemporary Accounting Research, 21, 885–924.

Rubin, A., Segal, B., and Segal, D., 2017. The interpretation of unanticipated news arrival and analysts' skill. Journal of Financial and Quantitative Analysis 52, 1491-1518.

Rubin, A., and Segal, D., 2016. The Discovery Role of Analysts. Working paper.

Appendix A Variable Definitions

Variable	Definition
analyst forecast variables	
afe	Analyst forecast error (in percentage) is measured as the absolute value of forecast error calculated as 100 times the difference between an analyst's last one-year ahead forecast and a firm's actual earnings (as reported in I/B/E/S) for year t divided by the latest monthly stock price from Compustat for year *t*.
afeup	Absolute value of positive forecast error when forecast error as defined above is greater than 0.
afedown	Absolute value of negative forecast error when forecast error as defined above is less than 0.
market reaction variables	
car3	Sum of daily market -adjusted abnormal return during three days event window around analyst earnings forecast date (i.e., -1 to +1 with day 0 as analyst earnings forecast date); analyst forecast date from I/B/E/S.
car7	Sum of daily market -adjusted abnormal return during five days event window around analyst earnings forecast date (i.e., -1 to +5 with day 0 as analyst earnings forecast date); analyst forecast date is from I/B/E/S.
analyst private information source variables	
private1	Number of private information source equal to 1 if an analyst obtains new information from one private source when making forecasts, and 0 otherwise.
private2	Number of private information source equal to 1 if an analyst obtains new information from two private sources when making forecasts, and 0 otherwise.
mgt	Equal to 1 if an analyst report has new information obtained from management sources such as personal meetings, site visits/tours, conference calls, and investor/analyst meeting days, and 0 otherwise.
meeting	Equal to 1 if an analyst report has new information obtained from personal meetings with managements, and 0 otherwise.
tour	Equal to 1 if an analyst report has new information obtained from site visits/tours, and 0 otherwise.
call	Equal to 1 if an analyst report has new information obtained from conference calls with management, and 0 otherwise.
invtday	Equal to 1 if an analyst report has new information obtained from investor /analyst meeting days, and 0 otherwise.
nonmgt	Equal to 1 if an analyst report has new information obtained from non-management sources such as customer surveys, supply chain checks (i.e., channel checks) and industry conferences, and 0 otherwise.
survey	Equal to 1 if an analyst report has new information obtained from customer surveys, and 0 otherwise.
channel	Equal to 1 if an analyst report has new information obtained from supply chain check (i.e. channel checks), and 0 otherwise.
conference	Equal to 1 if an analyst report has new information obtained from industry conferences, and 0 otherwise.
control variables	
buy	Equal to 1 for a strong buy or a buy recommendation, and 0 otherwise.
sell	Equals to 1 for a strong sell or a sell recommendation, and 0 otherwise.
Δ*recom*	Change in recommendation by calculating a difference between a current and a previous recommendation issued within the past year by the same analyst for the same firm.
brsize	Number of analysts employed at the brokerage firm.

firmexp	Firm experience, calculated as the number of years for which an analyst supplies a forecast for the firm.
industryexp	Industry experience, measured as the number of years since an analyst covered the firm's industry.
firm_covered	Number of firms covered is defined as the number of firms an analyst follows.
industry_covered	Number of industries covered is calculated as the number of industries an analyst follows.
horizon	Number of days between a forecast date and a forecast period end date (i.e., a fiscal year-end date).
logmv	Natural logarithm of firm's market capitalization in U.S. $ million, i.e., common shares outstanding multiplied by the fiscal year-end price.
mb	Ratio of market value to book value of a firm at year-end.
roa	Ratio of income before extraordinary items to total assets at the end of year t.
leverage	Total liabilities divided by total assets at year-end
retstd12	Standard deviation of daily stock return for a firm during 12 months prior to an analyst forecast date.
loss	Equal to 1 if a firm has a negative earnings during three fiscal years prior to an analyst forecast, and 0 otherwise
lognanalyst	Natural logarithm of the number of analysts following the firm in the previous year.
iholding	Institutional holding is measured as the total number of shares held by institutions divided by shares outstanding at the end of the same quarter. The percentage holdings of institutional investors are 0 if no institutional investor reports positive holdings for a firm-quarter.
readability	Aggregate annual report (i.e., Form 10-K) readability measure of Fog, Flesch-Kincaid, Flesch Reading Ease, and Smog Readability Index by multiplying the first two and the last one by negative one to ensure that all components are increasing in readability, ranking each component into percentiles from 1 to 100, and then taking the average across the four components. The higher readability, the easier to read.
connection	Equal to 1 for the analyst has any of client, investment, brokerage, and/or ownership relationship with the covered firm, and 0 otherwise.

Appendix B Definitions and Examples of Analyst Efforts (variable names in parentheses)

Information from Non-publicly Available Sources

Information from Management Sources (mgt)

Personal Meeting with Management (*meeting*)

Examples We **hosted** a NDR with Dawnrays' **management**.
Yesterday, we **met** with Nick Winser, Grid's **Executive Director** for the UK…
We **visited** with Humana's **management** team at the company's headquarters in Louisville on October 8.
Our **talks** with **management** indicated the big variance to our forecasts could derive chiefly from OPEX.
We had **breakfast** with new Sirius **CEO** Joseph Clayton.
We **talked** to the **CFO** of Redecard after the release of the company's 1Q12 results.
We recently **spent time** marketing in Europe with BMO's new **COO,** Bill Downe.

Site Visit/Tour (*tour*)

Examples We attended a **site visit** to Anooraq's Bokoni Platinum Mines in South Africa.
We **visited** CSKY's **plant** in Quanzhou City.
A few key takeaways from the LaRonde mine **analyst trip.**

Conference Call with Management (*call*)[38]

Examples Yesterday we hosted a **Conference Call with** Texas Instruments' **CEO,** Rich Templeton. (Closed to the public)
In yesterday's 4Q12 **Conference Call**, ESV's stated guidance for a 19% y/y increase in contract drilling expense was based off of the newly restated FY12 expense figure ($2,028mn), rather than from the sum of the prior quarters. (Open to the public)

Investor/Analyst Meeting (*invtday*)

Examples On Friday (6/1), MDT held an **investor day** in NY.
On Friday DB hosted a day of **investor meeting** with Shire management in the USA.
We recently hosted **investor meetings** with JBL CFO (Forbes Alexander) in NYC.
SMIC recently hosted an **analyst day** in Beijing.
We attended Sihuan's **analyst briefing** and came away with more confidence in its prospects for 2012.
We attended a group **analyst meeting** with management.

Information from Non-Management Sources (nonmgt)

Survey (*survey*)

Examples In January 2004, UBS conducted a **survey**, through Computerwire, of 100 European customers of SAP.
This morning, Statistical **surveys** released January retail data.
J.P. Morgan's monthly **survey** of US physician offices has tracked a spectacular decline in physician visits over the majority of 2011.

Channel Check (*channel*)

Examples Recent industry **channel checks** and data points, including Robert Half's just released Q1 results, make us confident that demand for permanent placement services has remained strong as CY05 has progressed.
Ahead of Merck's Q2:08 results (23 July), our **channel checks** in the liquid crystal (LC) space indicate some mixed signals including a reduction in demand for large LC panels, increased pricing pressure and some downgrades to production guidance.

Industry Conference (*conference*)

Examples This year's **energy conference** will be held in New York City.
The **Transcatheter Valve Therapies** (TVT) **conference** in Seattle will finish up on June 5.

Information from Publicly Available Sources

Post-earnings Announcement (*ea*)

[38] A conference call might be either open or closed to anyone (Bushee, Matsumoto, and Miller, 2003). I separately test sample excluding it from private information sources, and find that the results are qualitatively similar.

Examples	VMED has **reported Q4 results**.
	Mitsui Fudosan **announced 3Q FY2012 results** after the close of trading on February 6.
	3QFY12 results **beat expectations**.
	EPS were **in-line with** our **forecast**.
	Ipsos **guided** that FY 2003 results (due March 23) will show a further rise in operating margin.
	In yesterday's 4Q12 **conference call**, ESV's stated **guidance** for a 19% y/y increase in contract drilling expense was based off of the newly restated FY12 expense figure ($2,028mn), rather than from the sum of the prior quarters.
Pre-earnings Announcement (*preea*)	
Examples	We **forecast** revenue will grow 14% annually in both 2012 and 2013.
	We **expect F2Q results** to be good enough.
	We **preview** SIP ahead of the release of its FY12 result on 22 March 2012.
Non-Earnings Announcement (*nonea*)	
Examples	We believe the **resignation** of Carly Fiorina as Chairman and CEO signals that the board is ready to take more aggressive actions to create shareholder value.
	Devon Energy Announces **Merger** with Santa Fe Snyder.
	MFC announced a **hostile offer** to **acquire** the CL shares.
	GMR announced that it initiates a **cash dividend** policy and plans to declare its initial dividend following the first quarter earnings results.
	We **initiate coverage** of MCE with an Overweight (V) rating.
	A tentative **legal settlement** reached earlier this month in U S District Court in Boston.
	Gluskin Sheff Associates raised million for selling shareholders in an **initial public offering (IPO)** that closed May.
	In the last two weeks we have seen two major developments in US power **emissions regulation**.
	In Nov., EDU launched a **new product**.
	Renesas officially announced details of its **restructuring plan** including cutting its workforce by about completely outsourcing mass production of advanced process technology products to overseas foundries.
	VRTS **shares are down** over the last trading sessions largely attributable to concerns that a slowdown at SUNW could have a material impact on VRTS's business in coming quarters.
	This is a significant **new customer** win for MONI.

Appendix C Distribution by Bank (sorted by *afe*)

Bank	N (Obs)	N (Firm)	N (Analyst)	*private1*	*private2*	*afe*	*car3*	*car7*
UBS	15,054	1,608	374	0.139	0.002	1.613	-1.685	-2.873
J.P. Morgan	12,191	1,341	209	0.172	0.006	1.139	-1.401	-2.405
Credit Suisse	11,985	1,713	347	0.155	0.004	1.424	-1.633	-2.807
Citibank	9,801	1,247	199	0.156	0.002	1.491	-1.820	-2.989
RBC Capital Markets	9,727	1,349	162	0.119	0.003	1.495	-1.404	-2.357
Morgan Stanley	9,659	1,370	323	0.149	0.001	1.321	-1.748	-3.070
Deutsche Bank	9,483	1,448	279	0.167	0.002	1.510	-1.571	-2.793
Jefferies	3,516	712	95	0.097	0.001	1.496	-0.917	-1.595
HSBC	192	77	30	0.068	0.005	2.133	-2.519	-3.824
TD Securities	154	22	12	0.091	0.000	3.169	-1.833	-3.904
Overall	*81,762*	*10,887*	*2,030*	*0.131*	*0.003*	*1.679*	*-1.653*	*-2.862*

Table 1 Descriptive Statistics

Panel A: By Main Variable

This panel reports the summary statistics of the 81,762 analyst-firm-year observations during 2000-2014. All continuous variables are winsorized at 1 and 99 percentiles. See Appendix A for all variable definitions.

Variable	N (Obs)	Mean	Std Dev	Q1	Median	Q3
private1	81,762	0.148	0.356	0.000	0.000	0.000
private2	81,762	0.003	0.054	0.000	0.000	0.000
afe	81,762	1.438	4.431	0.075	0.263	0.888
afeup	32,156	2.745	8.977	0.120	0.434	1.520
afedown	45,190	0.862	2.117	0.083	0.239	0.686
car3	81,762	-1.581	6.222	-4.298	-1.323	1.298
car7	81,762	-2.709	7.906	-6.604	-2.423	1.449
buy	81,762	0.536	0.499	0.000	1.000	1.000
sell	81,762	0.063	0.243	0.000	0.000	0.000
Δ*recom*	81,762	0.003	0.100	0.000	0.000	0.000
brsize	81,762	218.520	117.380	126.000	173.000	342.000
firmexp	81,762	3.364	3.265	0.781	2.326	5.046
industryexp	81,762	4.562	3.384	1.786	3.827	6.723
firm_covered	81,762	17.070	7.540	12.000	16.000	21.000
industry_covered	81,762	2.854	1.714	2.000	2.000	4.000
horizon	81,762	146.590	97.140	65.000	152.000	243.000
logmv	81,762	8.455	1.628	7.301	8.396	9.597
mb	81,762	3.772	5.057	1.548	2.590	4.348
roa	81,762	0.089	0.102	0.043	0.087	0.139
leverage	81,762	0.568	0.234	0.405	0.570	0.730
retstd12	81,762	0.023	0.013	0.014	0.019	0.028
loss	81,762	0.159	0.366	0.000	0.000	0.000
lognanalyst	81,762	2.529	0.623	2.197	2.639	2.944
iholding	81,762	0.496	0.378	0.000	0.647	0.854
readability	48,786	37.077	22.654	18.250	33.500	53.500

Panel B: By Information Source

This panel shows the descriptive statistics of the 81,762 analyst-firm-year observations by both private and public information sources in the sample period 2000-2014. The first seven variables are proxies for private information sources. All continuous variables are winsorized at 1 and 99 percentiles. See Appendix A for the variable definitions of private information sources, and Section 3 for those of public information sources.

Variable	N (Obs)	N (Firm)	N (Analyst)	Mean	Std Dev	Q1	Median	Q3
meeting	81,762	987	588	0.028	0.000	0.164	0.000	0.000
tour	81,762	357	269	0.007	0.000	0.081	0.000	0.000
call	81,762	812	461	0.023	0.000	0.151	0.000	0.000
invtday	81,762	1,407	1,001	0.082	0.000	0.275	0.000	0.000
survey	81,762	20	13	0.000	0.000	0.019	0.000	0.000
channel	81,762	111	87	0.002	0.000	0.043	0.000	0.000
conference	81,762	486	296	0.012	0.000	0.109	0.000	0.000
ea	81,762	3,505	1,831	0.776	1.000	0.417	1.000	1.000
preea	81,762	2,403	1,334	0.162	0.000	0.369	0.000	0.000
nonea	81,762	1,921	1,131	0.093	0.000	0.290	0.000	0.000

Table 2 Sample Distribution By Year and Industry

Panel A: By Year

This panel displays the sample distribution by year of the 81,762 analyst-firm-year observations in the sample period 2000-2014. The first three in Overall represent the sum of the number of observations, firms, and analysts, respectively, and the rest are an average value for *private1, private2, afe, car3, and car7*, respectively. See Appendix A for all variable definitions.

Year	N (Obs)	N (Firm)	N (Analyst)	*afe*	*private1*	*private2*	*car3*	*car7*
2000	2,656	1,014	385	1.601	0.136	0.002	-2.293	-3.761
2001	4,567	1,258	436	1.976	0.131	0.002	-1.731	-2.787
2002	4,122	1,168	436	1.892	0.152	0.003	-2.168	-3.310
2003	5,492	1,269	502	1.061	0.156	0.002	-1.238	-2.159
2004	6,124	1,417	537	0.896	0.145	0.002	-1.089	-1.961
2005	7,133	1,510	541	1.164	0.130	0.002	-1.195	-2.013
2006	5,109	1,386	455	1.340	0.142	0.002	-1.294	-2.318
2007	4,865	1,337	447	1.604	0.146	0.002	-1.373	-2.517
2008	5,101	1,334	448	2.829	0.139	0.002	-2.467	-4.042
2009	5,496	1,353	440	2.156	0.152	0.004	-1.715	-3.234
2010	6,043	1,375	462	1.193	0.165	0.003	-1.157	-2.196
2011	7,741	1,461	482	1.208	0.153	0.005	-1.724	-3.034
2012	7,684	1,481	489	1.307	0.155	0.004	-1.558	-2.621
2013	7,634	1,482	453	1.006	0.160	0.004	-1.580	-2.539
2014	1,995	966	341	0.856	0.148	0.002	-2.348	-4.096
Overall	*81,762*	*19,811*	*6,854*	*1.473*	*0.147*	*0.003*	*-1.662*	*-2.839*

Panel B: By Industry

This panel shows the sample distribution of the 81,762 analyst-firm-year observations in the sample period 2000-2014 based on 24 Global Industry Classification Standard (GICS) codes. See Panel A of Table 2 for Overall, and Appendix A for all variable definitions.

Industry	N (Obs)	N (Firm)	N (Analyst)	*private1*	*private2*	*afe*	*car3*	*car7*
Energy	5,968	318	178	0.130	0.000	1.637	-1.555	-2.796
Materials	4,759	182	188	0.129	0.001	1.555	-1.638	-2.634
Capital Goods	5,341	215	191	0.161	0.002	1.013	-1.121	-2.017
Commercial & Professional Services	1,817	90	108	0.127	0.001	0.898	-1.400	-2.194
Transportation	2,027	78	67	0.149	0.001	2.380	-1.820	-2.804
Automobiles & Components	953	26	63	0.127	0.001	1.646	-2.029	-3.501
Consumer Durables & Apparel	1,737	85	97	0.148	0.003	1.864	-0.132	-0.505
Consumer Services	3,733	136	123	0.156	0.003	0.986	-1.507	-2.477
Media	3,100	108	140	0.094	0.002	2.066	-1.507	-2.807
Retailing	4,154	161	165	0.151	0.007	0.903	-1.952	-3.308
Food & Staples Retailing	1,484	30	50	0.152	0.005	0.759	-2.188	-3.820
Food, Beverage & Tobacco	1,947	70	70	0.105	0.001	0.552	-1.574	-2.815
Household & Personal Products	667	23	26	0.132	0.001	0.510	-0.951	-1.451
Health Care Equipment & Services	7,288	283	181	0.156	0.001	0.738	-1.246	-2.258
Pharmaceuticals, Biotechnology & Life Sciences	5,311	290	155	0.220	0.005	1.163	-1.636	-2.644
Banks	3,254	169	78	0.146	0.003	2.735	-2.259	-3.686
Diversified Financials	2,685	170	164	0.134	0.004	2.006	-1.631	-2.776
Insurance	1,851	80	64	0.207	0.004	1.745	-1.351	-2.338
Real Estate	278	43	66	0.072	0.000	2.643	-1.871	-3.244
Software & Services	8,274	447	320	0.160	0.004	1.334	-1.194	-2.203
Technology Hardware & Equipment	4,863	212	209	0.168	0.008	1.774	-1.874	-2.925
Semiconductors & Semiconductor Equipment	4,335	138	130	0.156	0.002	1.781	-2.713	-4.611
Telecommunication Services	1,936	89	96	0.112	0.001	2.623	-1.516	-2.804
Utilities	2,109	86	75	0.108	0.002	0.981	-1.268	-2.152
Other	1,891	114	134	0.080	0.001	1.615	-1.900	-3.304
Overall	*81,762*	*3,643*	*3,138*	*0.139*	*0.003*	*1.516*	*-1.593*	*-2.723*

Table 3 Pearson Correlation

This table provides the Pearson correlation matrix among the variables of the 81,762 analyst-firm-year observations in the sample period 2000-2014. The correlations marked in bold are significant (two-sided p < 0.01); the correlations in italics are statistically insignificant (two-sided p > 0.10). All continuous variables are winsorized at 1 and 99 percentiles. See Appendix A for all variable definitions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) afe																		
(2) car3	***-0.048***																	
(3) car7	***-0.057***	***0.870***																
(4) private1	***-0.011***	***0.017***	***0.011***															
(5) private2	***-0.007***	0.005	0.005	***-0.023***														
(6) brsize	***-0.027***	-0.003	-0.006	**0.036**	**0.013**													
(7) firmexp	***-0.051***	***-0.035***	***-0.044***	***0.019***	0.000	***0.035***												
(8) industryexp	***-0.047***	***-0.008***	***-0.014***	***0.016***	**0.000**	***0.105***	***0.547***											
(9) firm_covered	-0.003	0.002	0.006	***-0.030***	***-0.007***	***0.048***	***0.213***	***0.372***										
(10) industry_covered	0.004	0.003	0.002	-0.001	0.001	0.004	0.002	-0.005	***-0.009***									
(11) horizon	***0.091***	***0.006***	0.004	***0.020***	0.005	***0.018***	-0.003	-0.004	***0.007***	-0.002								
(12) logmv	***-0.206***	***-0.090***	***-0.133***	***0.101***	***0.010***	***0.096***	***0.224***	***0.147***	***-0.064***	***-0.009***	***0.039***							
(13) mb	***-0.090***	***0.016***	***0.015***	***0.021***	0.005	***0.025***	***-0.047***	***-0.038***	***-0.059***	-0.003	-0.002	***0.082***						
(14) roa	***-0.238***	0.001	0.004	***-0.011***	***-0.006***	***0.026***	***0.064***	***0.046***	***-0.040***	-0.001	***0.015***	***0.155***	***0.138***					
(15) leverage	***0.070***	***-0.019***	***-0.030***	0.006	-0.005	***0.035***	***0.099***	***0.069***	***0.058***	0.000	***-0.018***	***0.019***	***-0.010***	***-0.095***				
(16) retstd12	***0.260***	***-0.042***	***-0.054***	***-0.014***	0.004	***-0.009***	***-0.199***	***-0.198***	***-0.069***	***0.008***	***-0.009***	***-0.183***	***0.017***	***-0.286***	***-0.149***			
(17) loss	***0.214***	***-0.006***	*-0.004*	0.002	0.003	***-0.030***	***-0.110***	***-0.080***	***-0.018***	0.003	-0.003	***-0.155***	***0.037***	***-0.529***	***-0.116***	***0.368***		
(18) lognanalyst	***-0.112***	***-0.099***	***-0.139***	***0.071***	***0.015***	***0.081***	***0.196***	***0.162***	***-0.032***	***-0.007***	***0.037***	***0.640***	***0.048***	***0.163***	***-0.044***	***-0.209***	***-0.136***	
(19) iholding	***-0.029***	***0.033***	***0.045***	***-0.011***	0.005	***-0.029***	***-0.067***	***-0.083***	***-0.048***	0.004	***-0.006***	***-0.114***	***0.011***	***0.000***	***-0.039***	***0.040***	***0.037***	***-0.117***

Table 4 Sample Distribution by Private Information Source

Panel A: By Level

This panel displays the sample distribution by the level of private information sources of the 81,762 analyst-firm-year observations in the sample period 2000-2014. Source level depends on the number of private information sources. Thus, Source level=0 means that forecasts are made using public information sources only, whereas , Source level=1 (2) means that forecasts are made using one (two) private information source(s). See Appendix A for all variable definitions.

Level of private information source	N (Obs)	Percent
0	69,387	84.86
1	12,134	14.84
2	241	0.29
Total	*81,762*	*100.00*

Panel B: By Type

This panel reports the sample distribution by the type of private information sources of the 81,762 analyst-firm-year observations in the sample period 2000-2014. Source level depends on the number of private information sources. Thus, Source level=1 (2) (*private1*(*2*)) means that forecasts are made using one (two) private information source(s). Source types include *meeting*, *tour*, *call*, and *invtday* from *mgt*, and *survey*, *channel*, and *conference* from *nonmgt*. See Appendix A for all variable definitions.

Source level=1 (*private1*)			
Type of private information source		N (Obs)	Percent
mgt		***11,067***	***91.21***
invtday		6,534	53.85
meeting		2,145	17.68
call		1,875	15.45
tour		513	4.23
nonmgt		***1,067***	***8.79***
conference		896	7.38
channel		142	1.17
survey		29	0.24
Total		*12,134*	*100.00*
Source level=2 (*private2*)			
(A)	(B)	N (Obs) [(A)+(B)]	Percent
mgt	mgt	146	60.58
mgt	nonmgt	94	39.00
nonmgt	nonmgt	1	0.41
Total		*241*	*100.00*

Panel C: Detailed Distribution by Source Level=2

This panel provides the detailed sample distribution by two sources of private information of the 81,762 analyst-firm-year observations in the sample period 2000-2014. Source level depends on the number of private information sources. Thus, Source level=2 (*private2*) means that forecasts are made using two private information sources. Source types include *meeting*, *tour*, *call*, and *invtday* from *mgt*, and *survey*, *channel*, and *conference* from *nonmgt*. *meetinginvtday* represents forecasts based on two management-related private information sources from both personal meetings with management and investor/analyst days. See Appendix A for all variable definitions.

		Source level=2 (*private2*)							
Variable	Source	N (obs)	N (firm)	N (analyst)	Mean	Std Dev	Q1	Median	Q3
meetinginvtday	*mgt+mgt*	96	80	54	0.001	0.034	0.000	0.000	0.000
invtdayconference	*mgt+nonmgt*	72	65	41	0.001	0.030	0.000	0.000	0.000
meetingtour	*mgt+mgt*	17	14	16	0.000	0.014	0.000	0.000	0.000
tourinvtday	*mgt+mgt*	12	12	11	0.000	0.012	0.000	0.000	0.000
callinvtday	*mgt+mgt*	11	10	9	0.000	0.012	0.000	0.000	0.000
callconference	*mgt+nonmgt*	11	8	7	0.000	0.012	0.000	0.000	0.000
meetingcall	*mgt+mgt*	10	10	10	0.000	0.011	0.000	0.000	0.000
meetingconference	*mgt+nonmgt*	4	4	4	0.000	0.007	0.000	0.000	0.000
invtdaychannel	*mgt+nonmgt*	3	2	1	0.000	0.006	0.000	0.000	0.000
meetingchannel	*mgt+nonmgt*	3	3	2	0.000	0.006	0.000	0.000	0.000
callchannel	*mgt+nonmgt*	1	1	1	0.000	0.003	0.000	0.000	0.000
channelconference	*nonmgt+nonmgt*	1	1	1	0.000	0.003	0.000	0.000	0.000
Overall		*241*	*210*	*157*	*0.000*	*0.013*	*0.000*	*0.000*	*0.000*

Table 5 Univariate Comparison of Private Information Source

Panel A: By Level

This panel shows the mean comparisons by the level of private information sources of the 81,762 analyst-firm-year observations in the sample period 2000-2014. Source level depends on the number of private information sources. Thus, Source level=0 means that forecasts are made using public information sources only, whereas Source level=1 (2)) (*private1*(*2*)) means that forecasts are made using one (two) private information source(s). N (obs) means the number of observations while diff represents a difference. *diff (1-0)* shows the difference between one private and no private information source. See Appendix A for all variable definitions.

	Source level=0		**Source level=1 (*private1*)**		**Source level=2 (*private2*)**				
	N (obs)	**Mean**	N (obs)	**Mean**	N (obs)	**Mean**	***diff (1-0)***	***diff (2-0)***	***diff (2-1)***
afe	69,387	**1.460**	12,134	**1.327**	241	**0.868**	**-0.133*****	**-0.592*****	**-0.459***
afeup	27,473	**2.754**	4,594	**2.715**	89	**1.384**	**-0.039**	**-1.370**	**-1.331**
afedown	38,188	**0.882**	6,873	**0.757**	129	**0.666**	**-0.125*****	**-0.216**	**-0.091**
car3	69,387	**-1.627**	12,134	**-1.332**	241	**-0.973**	**0.295*****	**0.654**	**0.359**
car7	69,387	**-2.747**	12,134	**-2.505**	241	**-2.051**	**0.242*****	**0.696**	**0.455**

Panel B: By Level and Type

This panel shows the mean comparisons by the level and type of private information sources of the 81,762 analyst-firm-year observations in the sample period 2000-2014. Source level depends on the number of private information sources. Thus, Source level=0 means that forecasts are made using public information sources only, whereas Source level=1 (2) means that forecasts are made using one (two) private information source(s). Source types include *meeting*, *tour*, *call*, and *invtday* from *mgt*, and *survey*, *channel*, and *conference* from *nonmgt*. N (obs) means the number of observations while diff represents a difference. *diff (1-0)* shows the difference between one private and no private information source. See Appendix A for all variable definitions.

	Source level=1 (*private1*)					**Source level=2 (*private2*)**				
	mgt		nonmgt			mgt+mgt		mgt+nonmgt		
	N (obs)	**Mean (A)**	N (obs)	**Mean (B)**	***diff (B-A)***	N (obs)	**Mean (A)**	N (obs)	**Mean (B)**	***diff (B-A)***
afe	11,067	**1.301**	1,067	**1.595**	**0.294****	146	**0.931**	94	**0.770**	**-0.162**
afeup	4,246	**2.709**	348	**2.789**	**0.079**	58	**1.420**	31	**1.317**	**-0.102**
afedown	6,217	**0.714**	656	**1.165**	**0.451*****	74	**0.725**	54	**0.583**	**-0.142**
car3	11,067	**-1.350**	1,067	**-1.139**	**0.211**	146	**-1.267**	94	**-0.559**	**0.708**
car7	11,067	**-2.553**	1,067	**-2.008**	**0.545****	146	**-2.406**	94	**-1.522**	**0.884**

Table 6 Private Research Effort and Earnings Forecasts Error

This table reports multiple OLS regression results on the effect of the level of private information sources on analyst forecast error.

$$dependent=\beta_0 + \beta_1 private1 + \beta_2 private2 + \beta_3 analyst + \beta_4 firm + \beta_5 industy\ FE + \beta_6 bank\ FE + \beta_7 year\ FE + \varepsilon$$

The dependent variable is *dependent* which is absolute forecast error (*afe* in percentage), measured as the absolute value of forecast error calculated as 100 times the difference between an analyst's last one-year ahead forecast and a firm's actual earnings (as reported in I/B/E/S) for year t divided by average monthly stock price for year *t*. The key variables of interest (*private1* and *private2*) are the proxies for analysts' private research effort levels measured as the number of private information sources (i.e., *meeting*, *tour*, *call*, *invtday*, *survey*, *channel*, and *conference*). The rest of variables control for factors which influence the dependent variable. All the independent variables are measured in year *t-1* or year *t*. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry, year, and bank dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for firm-and year-level clustering. See Appendix A provides variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	afe	*afe*	*afeup*	*afeup*	*afedown*	*afedown*
private1	0.064	0.046	0.154	0.124	-0.013	-0.023
	(1.54)	(1.16)	(1.12)	(0.89)	(-0.32)	(-0.54)
private2	-0.448***	-0.488***	-0.950***	-1.024***	-0.155	-0.186*
	(-2.73)	(-2.95)	(-2.60)	(-2.88)	(-1.56)	(-1.83)
brsize		-0.001		-0.001		-0.001
		(-1.09)		(-0.75)		(-0.75)
firmexp		0.015		0.007		0.014***
		(1.60)		(0.22)		(3.13)
industryexp		-0.011		0.006		-0.016***
		(-1.04)		(0.17)		(-2.72)
firm_covered		-0.004		0.003		-0.004*
		(-1.10)		(0.29)		(-1.66)
industry_covered		0.002		0.009		0.004
		(0.22)		(0.28)		(0.92)
horizon		0.004***		0.006***		0.003***
		(9.15)		(5.75)		(11.08)
logmv	-0.299***	-0.316***	-0.479***	-0.508***	-0.196***	-0.207***
	(-4.76)	(-4.81)	(-2.87)	(-2.90)	(-6.37)	(-6.66)
mb	-0.056***	-0.055***	-0.137***	-0.136***	-0.020***	-0.019***
	(-5.91)	(-5.75)	(-5.20)	(-5.14)	(-4.03)	(-3.96)
roa	-4.038***	-4.080***	-6.652***	-6.891***	-2.732***	-2.689***
	(-4.56)	(-4.64)	(-3.68)	(-3.83)	(-5.61)	(-5.50)
leverage	1.935***	1.941***	4.176***	4.213***	0.940***	0.940***
	(6.03)	(6.05)	(4.46)	(4.45)	(5.37)	(5.34)
retstd12	72.929***	72.687***	138.479***	139.153***	34.352***	34.075***
	(8.68)	(8.30)	(7.81)	(7.56)	(8.06)	(7.82)
loss	0.913***	0.906***	1.760***	1.732***	0.556***	0.561***
	(4.52)	(4.50)	(4.14)	(4.12)	(4.56)	(4.52)
lognanalyst	0.131	0.132	-0.017	0.016	0.140**	0.133**
	(0.99)	(0.99)	(-0.05)	(0.05)	(2.09)	(2.03)
iholding	-0.589***	-0.598***	-1.181***	-1.188***	-0.302***	-0.310***
	(-5.15)	(-5.25)	(-3.96)	(-3.97)	(-5.26)	(-5.40)
constant	0.454	0.212	0.365	-0.264	0.545*	0.446
	(0.73)	(0.32)	(0.25)	(-0.17)	(1.68)	(1.25)

industry f.e.	yes	yes	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes	yes	yes
bank f.e.	yes	yes	yes	yes	yes	yes
clustering	firm-year	firm-year	firm-year	firm-year	firm-year	firm-year
observations	81,762	81,762	32,156	32,156	45,190	45,190
adjusted R^2	0.147	0.156	0.134	0.138	0.187	0.203

Table 7 Private Research Effort and Stock Market Reaction

This table reports multiple OLS regression results on the effect of the level of private information sources on stock market reaction to stock recommendations.

$dependent = \beta_0 + \beta_1 private1 + \beta_2 private2 + \beta_3 analyst + \beta_4 firm + \beta_5 industy\ FE + \beta_6 bank\ FE + \beta_7 year\ FE + \varepsilon$

The dependent variable is *dependent* which is cumulative abnormal return (*car*), measured as the sum of daily market-adjusted abnormal return during three (five) days event window around analyst earnings forecast date (i.e., -1 to +1 (+5) with day 0 as analyst earnings forecast date). *afeup* is defined as the absolute value of earnings forecast error when earnings forecast is greater than actual earnings, whereas *afedown* is opposite. The key variables of interest (*private1* and *private2*) are the proxies for analysts' private research effort levels measured as the number of private information sources (i.e., *meeting*, *tour*, *call*, *invtday*, *survey*, *channel*, and *conference*). The rest of variables control for factors which influence the dependent variable. All the independent variables are measured in year *t-1* or year *t*. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry, year, and bank dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for firm- and year-level clustering. See Appendix A provides variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)
	car3	*car3*	*car7*	*car7*
private1	0.495***	0.447***	0.602***	0.550***
	(7.02)	(6.67)	(6.96)	(6.50)
private2	0.928***	0.823**	1.163**	1.032**
	(2.78)	(2.45)	(2.53)	(2.19)
buy		0.464***		0.509***
		(6.41)		(5.35)
sell		-0.233**		-0.287**
		(-2.30)		(-1.96)
Δ*recom*		1.232***		1.264***
		(4.13)		(4.20)
afe		-0.063***		-0.096***
		(-6.45)		(-6.56)
brsize		0.001**		0.001
		(2.41)		(1.39)
firmexp		-0.049***		-0.062***
		(-3.43)		(-3.13)
industryexp		0.025**		0.031**
		(2.30)		(1.97)
firm_covered		-0.009		-0.011
		(-1.62)		(-1.43)
industry_covered		0.013		0.010
		(1.12)		(0.71)
horizon		0.001***		0.001***
		(3.32)		(3.73)
logmv	-0.320***	-0.359***	-0.624***	-0.673***
	(-5.67)	(-6.33)	(-6.32)	(-6.74)
mb	0.040***	0.033***	0.055***	0.046***
	(3.92)	(3.34)	(3.73)	(3.17)
roa	-0.463	-0.765	0.090	-0.361
	(-0.72)	(-1.14)	(0.10)	(-0.38)
leverage	-0.778***	-0.618**	-1.298***	-1.063**
	(-2.89)	(-2.26)	(-3.07)	(-2.55)
retstd12	-42.921***	-39.213***	-75.974***	-70.073***

	(-5.09)	(-4.47)	(-5.37)	(-4.85)
loss	-0.314*	-0.280	-0.389	-0.329
	(-1.83)	(-1.61)	(-1.50)	(-1.26)
lognanalyst	-0.707***	-0.670***	-1.145***	-1.100***
	(-5.89)	(-5.75)	(-6.44)	(-6.39)
iholding	0.231	0.180	0.367*	0.295
	(1.59)	(1.24)	(1.75)	(1.40)
constant	2.805***	2.431**	5.471***	5.166***
	(2.86)	(2.49)	(3.55)	(3.37)
industry f.e.	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes
bank f.e.	yes	yes	yes	yes
clustering	firm-year	firm-year	firm-year	firm-year
observations	81,762	81,762	81,762	81,762
adjusted R^2	0.027	0.032	0.049	0.054

Table 8 Type of Private Information Sources

Panel A (B) shows multiple OLS regression results on the effect of the level and the type of private information sources on forecast error (market reaction to stock recommendations). The dependent variables for Panel A are absolute forecast errors (*afe*, *afeup*, and *afedown*) while those for Panel B are cumulative abnormal returns (*car3* and *car7*). The key variables of interest (*private1mgt, private1nonmgt*, *private2mgt* and *private2mixed*) are the proxies for analysts' private research effort levels measured as the number of private information sources (i.e., *meeting, tour*, *call*, *invtday*, *survey*, *channel*, and *conference*). *private1mgt* (*private1nonmgt*) are equal to 1 if analysts collect information from one management (non-management) source, and 0 otherwise. *private2mgt* (*private2mixedt*) are equal to 1 if analysts discover information from two (at least one) management (non-management) sources, and 0 otherwise. *meeting*, *tour*, *call*, and *invtday* are management sources, whereas *survey*, *channel*, and *conference* are non-management sources. There is only one combination of two non-management sources excluded from the regressions. The rest of variables control for factors which influence the dependent variable. All the independent variables are measured in year *t-1* or year *t*. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry, year, and bank dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for firm-and year-level clustering. See Appendix A provides variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

Panel A: Source Type and Earnings Forecast Error

	(1)	(2)	(3)	(4)	(5)	(6)
	afe	*afe*	*afeup*	*afeup*	*afedown*	*afedown*
private1mgt	0.085**	0.069*	0.219	0.189	-0.024	-0.031
	(2.00)	(1.73)	(1.26)	(1.08)	(-0.73)	(-0.90)
private1nonmgt	-0.150	-0.192	-0.650	-0.671	0.091	0.054
	(-0.60)	(-0.77)	(-0.90)	(-0.93)	(0.61)	(0.37)
private2mgt	-0.207	-0.270	-0.771*	-0.806*	0.092	0.027
	(-0.97)	(-1.15)	(-1.83)	(-1.94)	(0.47)	(0.13)
private2mixed	-0.839***	-0.841***	-1.296**	-1.443***	-0.504***	-0.488***
	(-3.45)	(-3.77)	(-2.25)	(-2.61)	(-4.56)	(-4.16)
brsize		-0.001		-0.001		-0.001
		(-1.08)		(-0.74)		(-0.75)
firmexp		0.015		0.007		0.014***
		(1.60)		(0.23)		(3.11)
industryexp		-0.011		0.006		-0.016***
		(-1.04)		(0.17)		(-2.72)
firm_covered		-0.004		0.003		-0.004*
		(-1.10)		(0.29)		(-1.66)
industry_covered		0.002		0.009		0.004
		(0.22)		(0.28)		(0.94)
horizon		0.004***		0.006***		0.003***
		(9.15)		(5.77)		(11.11)
logmv	-0.299***	-0.316***	-0.480***	-0.509***	-0.196***	-0.207***
	(-4.77)	(-4.82)	(-2.87)	(-2.90)	(-6.37)	(-6.66)
mb	-0.056***	-0.054***	-0.137***	-0.136***	-0.020***	-0.019***
	(-5.91)	(-5.76)	(-5.19)	(-5.13)	(-4.03)	(-3.96)
roa	-4.046***	-4.088***	-6.679***	-6.918***	-2.727***	-2.686***
	(-4.57)	(-4.66)	(-3.69)	(-3.84)	(-5.59)	(-5.49)
leverage	1.931***	1.937***	4.162***	4.199***	0.940***	0.940***
	(6.05)	(6.06)	(4.46)	(4.45)	(5.38)	(5.34)
retstd12	72.956***	72.716***	138.547***	139.222***	34.350***	34.075***
	(8.67)	(8.30)	(7.83)	(7.57)	(8.07)	(7.83)

loss	0.914***	0.907***	1.762***	1.734***	0.555***	0.561***
	(4.52)	(4.49)	(4.14)	(4.11)	(4.55)	(4.51)
lognanalyst	0.131	0.133	-0.018	0.015	0.140**	0.134**
	(0.99)	(1.00)	(-0.06)	(0.05)	(2.10)	(2.03)
iholding	-0.589***	-0.597***	-1.180***	-1.187***	-0.303***	-0.310***
	(-5.15)	(-5.25)	(-3.96)	(-3.96)	(-5.27)	(-5.40)
constant	0.455	0.212	0.376	-0.255	0.546*	0.447
	(0.73)	(0.32)	(0.26)	(-0.16)	(1.69)	(1.26)
industry f.e.	yes	yes	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes	yes	yes
bank f.e.	yes	yes	yes	yes	yes	yes
clustering	firm-year	firm-year	firm-year	firm-year	firm-year	firm-year
observations	81,762	81,762	32,156	32,156	45,190	45,190
adjusted R^2	0.147	0.156	0.134	0.138	0.187	0.204

Panel B Source Type and Stock Market Reaction to Stock Recommendations

	(1) *car3*	(2) *car3*	(3) *car7*	(4) *car7*
private1mgt	0.488***	0.444***	0.575***	0.527***
	(6.85)	(6.49)	(6.26)	(5.86)
private1nonmgt	0.568***	0.484***	0.880***	0.784***
	(3.10)	(2.72)	(3.52)	(3.18)
private2mgt	0.588*	0.483	0.768	0.643
	(1.73)	(1.38)	(1.32)	(1.08)
private2mixed	1.414***	1.305**	1.750***	1.606***
	(2.58)	(2.41)	(3.12)	(2.93)
buy		0.464***		0.508***
		(6.43)		(5.36)
sell		-0.234**		-0.287**
		(-2.30)		(-1.97)
Δ*recom*		1.232***		1.263***
		(4.13)		(4.21)
afe		-0.063***		-0.096***
		(-6.46)		(-6.56)
brsize		0.001**		0.001
		(2.41)		(1.39)
firmexp		-0.049***		-0.062***
		(-3.43)		(-3.14)
industryexp		0.025**		0.031**
		(2.30)		(1.97)
firm_covered		-0.009		-0.011
		(-1.62)		(-1.43)
industry_covered		0.013		0.010
		(1.12)		(0.71)
horizon		0.001***		0.001***
		(3.31)		(3.72)
logmv	-0.320***	-0.359***	-0.623***	-0.673***
	(-5.66)	(-6.31)	(-6.31)	(-6.73)
mb	0.040***	0.033***	0.054***	0.045***

	(3.92)	(3.33)	(3.72)	(3.15)
roa	-0.462	-0.764	0.099	-0.353
	(-0.72)	(-1.14)	(0.11)	(-0.37)
leverage	-0.776***	-0.616**	-1.293***	-1.059**
	(-2.88)	(-2.25)	(-3.05)	(-2.53)
retstd12	-42.941***	-39.231***	-76.012***	-70.112***
	(-5.09)	(-4.48)	(-5.37)	(-4.85)
loss	-0.314*	-0.280	-0.390	-0.330
	(-1.83)	(-1.61)	(-1.51)	(-1.26)
lognanalyst	-0.707***	-0.670***	-1.146***	-1.101***
	(-5.89)	(-5.76)	(-6.45)	(-6.39)
iholding	0.231	0.180	0.367*	0.295
	(1.60)	(1.24)	(1.75)	(1.40)
constant	2.804***	2.430**	5.469***	5.165***
	(2.86)	(2.49)	(3.55)	(3.37)
industry f.e.	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes
bank f.e.	yes	yes	yes	yes
clustering	firm-year	firm-year	firm-year	firm-year
observations	81,762	81,762	81,762	81,762
adjusted R^2	0.027	0.032	0.049	0.054

Table 9 Robustness Tests on Earnings Forecast Error

Panel A shows multiple OLS regression results on the effect of the level of private information sources on forecast error and market reaction. Panel (A) replicates the results of Table 6 and 7 using the readability level of annual reports (*readability*) and analysts' relationship with the covered firm (*connection*) as additional control variables. To create another dependent (control) variable, *afeact*, actual earnings is used to scale forecast error instead of average monthly stock price, and is included in Columns (2) ((5), and (6)) of Panel A for comparison with Columns (1), (3), and (4) of Panel A. Panel B reports multiple OLS regression results on the effect of the level of private information sources on forecast error. Panel B repeats the models in Table 6 using the mean values of all variables except for private information source variables. Panel B includes bank fixed effect and standard errors cluster-adjusted at bank level. Consistent with the findings of Table 6, more private information (*private2*) significantly decreases average forecast errors across the models. All the independent variables are measured in year *t-1* or year *t.* All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on bank dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for bank-level clustering. See Appendix A provides variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

Panel A: Additional Control Variables and A New Absolute Forecast Error

	(1)	(2)	(3)	(4)	(5)	(6)
	afe	*afeact*	*car3*	*car7*	*car3*	*car7*
private1	0.047	-0.000	0.410***	0.511***	0.406***	0.504***
	(0.85)	(-0.08)	(6.38)	(5.06)	(6.28)	(4.87)
private 2	-0.515***	-0.030***	0.986**	1.122**	1.003**	1.132**
	(-2.68)	(-2.71)	(2.49)	(1.96)	(2.48)	(1.99)
buy			0.459***	0.494***	0.460***	0.496***
			(5.54)	(4.70)	(5.57)	(4.69)
sell			-0.304**	-0.373**	-0.310**	-0.386**
			(-2.46)	(-2.04)	(-2.52)	(-2.08)
Δ*recom*			1.371***	1.263***	1.335***	1.214***
			(3.56)	(3.03)	(3.66)	(3.10)
afe			-0.070***	-0.109***		
			(-7.38)	(-6.77)		
afeact					-0.394***	-0.565***
					(-5.71)	(-6.67)
brsize	-0.000	-0.000	0.001	0.000	0.001	0.000
	(-0.67)	(-0.71)	(1.20)	(0.30)	(1.28)	(0.40)
firmexp	0.022*	0.002*	-0.046**	-0.057**	-0.047**	-0.059**
	(1.86)	(1.67)	(-2.48)	(-2.33)	(-2.55)	(-2.42)
industryexp	-0.025*	-0.004***	0.019	0.022	0.017	0.020
	(-1.93)	(-4.63)	(1.32)	(1.06)	(1.21)	(0.97)
firm_covered	-0.002	-0.000	-0.007	-0.008	-0.007	-0.007
	(-0.42)	(-0.51)	(-1.00)	(-0.78)	(-0.98)	(-0.75)
industry_covered	-0.005	0.000	0.017	0.018	0.019	0.020
	(-0.45)	(0.30)	(1.01)	(0.80)	(1.09)	(0.90)
horizon	0.005***	0.001***	0.001**	0.001***	0.001**	0.001***
	(10.01)	(11.05)	(2.19)	(2.62)	(2.34)	(2.65)
logmv	-0.294***	-0.028***	-0.346***	-0.647***	-0.342***	-0.640***
	(-3.79)	(-8.21)	(-4.78)	(-5.34)	(-4.74)	(-5.32)
mb	-0.071***	-0.002***	0.024*	0.030	0.027**	0.035*
	(-5.71)	(-2.59)	(1.91)	(1.64)	(2.07)	(1.82)
roa	-4.022***	-0.188***	-1.426*	-1.289	-1.277	-1.037
	(-3.94)	(-2.84)	(-1.71)	(-1.14)	(-1.54)	(-0.93)

leverage	2.044***	0.080***	-0.624**	-0.961**	-0.707**	-1.100**
	(5.40)	(3.89)	(-2.06)	(-2.06)	(-2.31)	(-2.30)
retstd12	74.538***	2.812***	-28.410***	-49.133***	-31.790***	-54.718***
	(7.98)	(8.53)	(-3.54)	(-3.97)	(-3.99)	(-4.38)
loss	0.669***	0.107***	-0.508**	-0.559*	-0.504**	-0.556*
	(3.09)	(7.29)	(-2.49)	(-1.95)	(-2.50)	(-1.95)
lognanalyst	0.356**	-0.000	-0.722***	-1.142***	-0.739***	-1.169***
	(1.97)	(-0.03)	(-5.06)	(-5.75)	(-5.20)	(-5.84)
iholding	-2.623***	-0.036	1.014***	1.471***	1.170***	1.715***
	(-4.73)	(-1.45)	(2.71)	(2.60)	(3.12)	(3.08)
readability	0.000	0.000	0.003	0.003	0.003	0.003
	(0.09)	(0.14)	(0.99)	(0.86)	(0.96)	(0.83)
connection	-0.077	0.007	-0.206	-0.194	-0.213	-0.197
	(-0.73)	(0.83)	(-1.44)	(-1.04)	(-1.49)	(-1.05)
constant	0.828	0.170***	1.598	3.618**	1.586	3.590**
	(1.07)	(4.38)	(1.57)	(2.25)	(1.55)	(2.23)
industry f.e.	yes	yes	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes	yes	yes
bank f.e.	yes	yes	yes	yes	yes	yes
clustering	firm-year	firm-year	firm-year	firm-year	firm-year	firm-year
observations	48,786	48,722	48,786	48,786	48,722	48,722
adjusted R^2	0.163	0.093	0.032	0.052	0.032	0.051

Panel B: Mean Value Regression of Forecast Error

	(1) *afemean*	(2) *afemean*	(3) *afeupmean*	(4) *afeupmean*	(5) *afedownmean*	(6) *afedownmean*
private1	-1.165	-1.180	-0.389	-0.773	-1.555*	-1.027
	(-1.44)	(-1.43)	(-0.23)	(-0.48)	(-1.93)	(-1.79)
private 2	-23.810*	-25.231**	-55.104**	-61.447***	-21.485*	-18.837*
	(-2.24)	(-2.68)	(-3.05)	(-3.47)	(-2.16)	(-1.88)
brsizemean		-0.006		-0.005		-0.004
		(-1.62)		(-1.05)		(-0.98)
firmexmean		0.218*		0.495**		0.019
		(1.97)		(3.06)		(0.34)
indusexmean		0.041		-0.011		-0.076
		(0.37)		(-0.05)		(-1.36)
ntickermean		-0.040		0.037		0.020
		(-1.42)		(0.55)		(0.74)
gindnmean		0.487		0.759		0.183
		(1.15)		(1.67)		(0.79)
horizonmean		0.005		0.008		-0.002
		(0.78)		(0.83)		(-0.41)
logmvmean	-0.786***	-0.841***	-1.147***	-1.497***	-0.112	-0.235
	(-3.92)	(-4.03)	(-3.69)	(-4.19)	(-0.59)	(-1.79)
mbmean	-0.140**	-0.128**	-0.069	-0.005	-0.029	0.023
	(-3.23)	(-2.72)	(-0.58)	(-0.04)	(-0.40)	(0.44)
roamean	-3.837	-4.274	-6.474	-8.319**	-3.186	-4.219
	(-1.16)	(-1.43)	(-1.58)	(-2.42)	(-0.74)	(-1.14)
leveragemean	5.843***	5.888***	8.876***	8.674***	5.401**	4.511**

	(3.96)	(3.96)	(4.54)	(4.88)	(2.73)	(3.07)
retstd12mean	118.844***	124.097***	110.766**	112.101**	176.092***	153.191***
	(6.24)	(7.58)	(2.72)	(2.93)	(4.12)	(3.41)
lossmean	2.215*	2.135*	2.468	2.033	1.213	0.347
	(1.89)	(1.89)	(0.81)	(0.80)	(0.47)	(0.18)
lognanalystmean	1.463**	1.399**	1.669**	1.609**	1.062**	0.972*
	(3.01)	(2.83)	(2.46)	(2.53)	(2.27)	(1.96)
iholdingmean	-3.457***	-3.665***	-1.427	-1.365	-2.264**	-2.140**
	(-4.12)	(-3.94)	(-0.90)	(-0.81)	(-2.59)	(-2.52)
constant	1.393	1.061	4.336	3.813	-5.681	-2.954
	(0.78)	(0.51)	(1.63)	(1.12)	(-1.34)	(-0.98)
industry f.e.	no	no	no	no	no	no
year f.e.	no	no	no	no	no	no
bank f.e.	yes	yes	yes	yes	yes	yes
clustering	bank	bank	bank	bank	bank	bank
observations	1,903	1,903	1,581	1,581	1,656	1,656
adjusted R^2	0.106	0.113	0.006	0.014	0.038	0.040

Table 10 Change analyses on Effect of Increase in Private Research Effort

This table reports multiple OLS regression results on the effect of increase in the level of private information sources on analyst forecast error. This table replicates the results of Table 6 and 7 using the change values of all variables between a current and previous forecast, and the change value of annual report readability (Δ*readability)* and the change value of analysts' relations with the covered firm (Δ*connection*) as additional control variables. The dependent variable is *privateincrease* equal to 1 if there is increase in the number of private information sources between a current and previous forecast. The key independent variables of interest are changes in absolute forecast error (*afechg*) and changes in cumulative abnormal returns (*car3chg* and *car7chg*). All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry, year, and bank dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for firm-and year-level clustering. See Appendix A provides variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	afechg	*afechg*	*car3chg*	*car3chg*	*car7chg*	*car7chg*
privateincrease	-0.010***	-0.010***	0.522***	0.529***	0.602***	0.722***
	(-3.19)	(-2.80)	(5.79)	(6.01)	(4.37)	(6.51)
Δ*buy*			0.209***	0.240***	0.216***	0.193**
			(5.05)	(4.20)	(3.90)	(2.46)
Δ*sell*			-0.165*	-0.205*	-0.221**	-0.305**
			(-1.90)	(-1.73)	(-2.30)	(-2.15)
Δ*recom*			0.985***	1.591***	0.910**	1.526***
			(3.01)	(3.60)	(2.30)	(3.13)
Δ*afe*			-0.011	-0.042	-0.029	-0.070**
			(-0.54)	(-1.63)	(-1.50)	(-2.35)
Δ*brsize*	0.000*	0.000	0.000	0.000	0.000	0.000
	(1.94)	(0.12)	(0.05)	(0.16)	(0.50)	(0.27)
Δ*firmexp*	0.000	-0.000	-0.025***	-0.020	-0.021**	-0.007
	(0.77)	(-0.14)	(-2.88)	(-1.48)	(-2.27)	(-0.47)
Δ*industryexp*	-0.000	-0.001	0.026***	0.026**	0.009	-0.000
	(-0.26)	(-1.61)	(2.83)	(2.08)	(0.89)	(-0.01)
Δ*firm_covered*	-0.001**	-0.001	-0.002	0.002	0.002	0.007
	(-2.41)	(-1.29)	(-0.47)	(0.33)	(0.42)	(0.76)
Δ*industry_covered*	-0.001	-0.001	0.006	0.006	0.006	0.009
	(-1.51)	(-1.59)	(0.52)	(0.42)	(0.48)	(0.53)
Δ*horizon*	0.002***	0.003***	0.000	0.000	0.000	0.000
	(30.88)	(32.73)	(1.23)	(0.52)	(0.96)	(0.73)
Δ*logmv*	-0.794***	-0.920***	-0.581**	-0.915***	-0.777**	-1.182***
	(-23.22)	(-23.31)	(-1.99)	(-2.62)	(-2.20)	(-2.75)
Δ*mb*	0.002	0.006***	-0.115***	-0.129**	-0.157***	-0.154***
	(1.05)	(2.71)	(-3.63)	(-2.49)	(-5.12)	(-2.84)
Δ*roa*	-0.012	0.042	-5.060***	-9.634***	-5.538**	-10.737***
	(-0.09)	(0.45)	(-2.70)	(-4.00)	(-2.40)	(-3.57)
Δ*leverage*	-0.064	-0.105	1.669**	1.096	1.662	1.228
	(-0.99)	(-1.24)	(2.11)	(1.06)	(1.58)	(1.09)
Δ*retstd12*	10.845***	11.053***	29.725	42.377*	39.408	44.130
	(6.63)	(6.89)	(1.47)	(1.86)	(1.46)	(1.46)
Δ*loss*	0.037**	-0.035	-0.573*	-1.080**	-0.567	-0.890*
	(2.15)	(-1.57)	(-1.94)	(-2.52)	(-1.41)	(-1.75)
Δ*lognanalyst*	0.101***	0.111***	-0.433***	-0.761***	-0.564***	-1.087***
	(5.02)	(5.87)	(-2.97)	(-3.23)	(-2.83)	(-3.37)

Δ*iholding*	-0.233***	-0.798***	-0.578***	1.982**	-0.643**	2.127**
	(-10.36)	(-10.46)	(-4.16)	(1.97)	(-2.17)	(2.15)
Δ*readability*		-0.003***		-0.008		-0.008
		(-7.12)		(-0.79)		(-0.56)
Δ*connection*		0.020***		-0.010		0.050
		(4.37)		(-0.12)		(0.64)
constant	0.032***	0.025***	-0.129*	-0.136	-0.076	-0.001
	(4.85)	(3.43)	(-1.66)	(-1.17)	(-0.88)	(-0.01)
industry f.e.	yes	yes	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes	yes	yes
bank f.e.	yes	yes	yes	yes	yes	yes
clustering	firm-year	firm-year	firm-year	firm-year	firm-year	firm-year
observations	78,150	45,425	78,150	45,425	78,150	45,425
adjusted R^2	0.095	0.096	0.003	0.005	0.003	0.005

Table 11 High Effort and Earnings Forecasts Error

This table replicates the results of Table 6 using the sample of analysts who do not use any private information sources in the first place, but use them afterwards. *high_type* is an indicator variable equal to 1 if the private information source level is greater than 0 after no private sources in the first place. This table reports multiple OLS regression results on analyst forecast error. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry, year, and bank dummies are not reported for brevity. The *t*-statistics in parentheses are based on standard errors adjusted for firm-and year-level clustering. See Appendix A provides variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	afe	*afe*	*afeup*	*afeup*	*afedown*	*afedown*
high_type	-0.302**	-0.278**	-0.348	-0.352	-0.223**	-0.201*
	(-2.25)	(-2.16)	(-1.45)	(-1.44)	(-2.14)	(-1.95)
brsize		-0.000		0.000		-0.000
		(-0.84)		(0.08)		(-0.79)
firmexp		0.017*		0.010		0.017***
		(1.81)		(0.34)		(3.89)
industryexp		-0.014		0.000		-0.017***
		(-1.59)		(0.01)		(-2.67)
firm_covered		-0.003		0.001		-0.004
		(-0.83)		(0.09)		(-1.36)
industry_covered		0.003		0.014		0.004
		(0.34)		(0.47)		(0.92)
horizon		0.004***		0.006***		0.003***
		(9.21)		(6.38)		(10.84)
logmv	-0.317***	-0.333***	-0.520***	-0.549***	-0.208***	-0.219***
	(-4.57)	(-4.61)	(-2.86)	(-2.89)	(-5.80)	(-6.05)
mb	-0.053***	-0.052***	-0.132***	-0.131***	-0.019***	-0.018***
	(-5.67)	(-5.55)	(-5.04)	(-4.95)	(-3.63)	(-3.62)
roa	-4.159***	-4.194***	-7.168***	-7.387***	-2.680***	-2.640***
	(-4.83)	(-4.94)	(-3.70)	(-3.85)	(-5.48)	(-5.41)
leverage	1.936***	1.944***	3.988***	4.026***	0.998***	0.998***
	(5.98)	(6.01)	(4.29)	(4.28)	(5.83)	(5.80)
retstd12	74.113***	73.905***	136.102***	136.861***	37.288***	37.039***
	(9.12)	(8.80)	(8.52)	(8.30)	(8.48)	(8.22)
loss	0.921***	0.914***	1.753***	1.729***	0.559***	0.564***
	(4.60)	(4.58)	(4.18)	(4.17)	(4.67)	(4.64)
lognanalyst	0.166	0.169	0.034	0.068	0.166**	0.160**
	(1.16)	(1.17)	(0.10)	(0.20)	(2.26)	(2.22)
iholding	-0.610***	-0.624***	-1.154***	-1.177***	-0.331***	-0.340***
	(-5.14)	(-5.26)	(-3.84)	(-3.87)	(-5.49)	(-5.65)
constant	0.744	0.440	1.244	0.459	0.612*	0.488
	(1.24)	(0.67)	(0.88)	(0.30)	(1.89)	(1.32)
industry f.e.	yes	yes	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes	yes	yes
bank f.e.	yes	yes	yes	yes	yes	yes
clustering	firm-year	firm-year	firm-year	firm-year	firm-year	firm-year
observations	69,387	69,387	27,473	27,473	38,188	38,188
adjusted R^2	0.148	0.158	0.134	0.138	0.192	0.208

Table 12 Determinants of Analysts' Private Research Efforts (Ordered Logit)

This table shows ordered logit regression results on the determinants of the level of proprietary information source (*private*), A categorical independent variable, *private*, is regressed on analyst- and firm-specific dependent variables from Panel A of Table 9 after adding more dependent variables as follows: analyst gender (*female*) equal to 1 if analyst is a female, and 0 otherwise; analyst location (*foreign*) equal to 1 if analyst resides outside of U.S., and 0 otherwise; analyst education level (*graduate*) equal to 1 if analyst holds a graduate degree, and 0 otherwise; *turnover* calculated as100 times the number of shares traded for a firm deflated by the total number of common shares outstanding in year *t*. Model 1 and 2 do not include any fixed effect without any clustering, whereas Model 3 and 4 contain all three fixed effects with firm clustering. All continuous variables are winsorized at the 1 and 99 percentiles. Coefficients on industry, year, and bank dummies are not reported for brevity. The *t*-statistics in parentheses of Model 3 and 4 are based on standard errors adjusted for firm-level clustering. See Appendix A provides variable definitions. *, **, and *** represent significance at 10%, 5%, and 1% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)
	Ologit			
	private	*private*	*private*	*private*
brsize	0.001***	0.001***	0.001***	0.001***
	(9.47)	(7.28)	(4.09)	(3.80)
firmexp	0.013***	-0.000	-0.000	-0.003
	(3.74)	(-0.10)	(-0.08)	(-0.45)
industryexp	0.011***	0.007*	-0.002	-0.002
	(3.03)	(1.85)	(-0.31)	(-0.26)
firm_covered	-0.016***	-0.012***	-0.011***	-0.011***
	(-11.92)	(-8.14)	(-5.95)	(-4.51)
industry_covered	-0.002	-0.001	-0.001	0.000
	(-0.38)	(-0.15)	(-0.12)	(0.02)
horizon	0.001***	0.000***	0.000***	0.000
	(5.46)	(4.64)	(2.97)	(1.27)
female	0.082***	0.067***	0.039	0.023
	(4.05)	(3.28)	(1.38)	(0.63)
foreign	-0.637***	-0.649***	-0.513***	-0.520**
	(-7.17)	(-7.23)	(-3.70)	(-2.49)
graduate	0.432***	0.345***	0.084	0.091
	(5.34)	(4.21)	(0.84)	(0.73)
connection	0.096***	0.091***	0.099**	0.120*
	(4.06)	(3.59)	(2.01)	(1.82)
logmv		0.192***	0.196***	0.203***
		(21.09)	(12.18)	(9.93)
mb		0.007***	0.005	0.004
		(3.48)	(1.53)	(1.08)
roa		-0.998***	-1.082***	-1.098***
		(-8.15)	(-5.19)	(-4.27)
retstd12		4.116***	3.469**	5.784***
		(4.53)	(2.30)	(3.00)
loss		0.076**	0.029	0.094
		(2.20)	(0.57)	(1.59)
lognanalyst		0.020	-0.018	-0.073
		(0.84)	(-0.44)	(-1.44)
iholding		0.058**	0.051	0.579***

		(2.14)	(1.09)	(4.49)
turnover		1.640	0.093	-2.211
		(1.16)	(0.04)	(-0.79)
readability				-0.002**
				(-2.13)
cut1				
constant	1.889***	3.644***	3.518***	3.575***
	(47.94)	(43.46)	(14.93)	(12.24)
cut2				
constant	5.995***	7.765***	7.652***	7.624***
	(80.42)	(73.78)	(31.39)	(25.33)
industry f.e.	no	no	yes	yes
year f.e.	no	no	yes	yes
bank f.e.	no	no	yes	yes
clustering	no	no	firm	firm
observations	81,757	80,687	80,687	48,539
adjusted R^2	0.006	0.018	0.031	0.037

Conclusion

This dissertation includes three different studies on the properties of analysts' research reports and firms' annual reports.

Based on textual analysis of 351,629 analyst reports for US firms over 2000-2014, the first essay investigates the determinants and consequences of analysts' research report length. Previous literature finds that management tends to write a longer annual report to hide/obfuscate bad news. On the contrary, using textual analysis, I find that analysts tend to write a longer analyst report to provide, not hide, more information to their investors, especially, when they write stock recommendation upgrades which are perceived to be less credible than stock recommendation downgrades. Previous studies argue that analysts tend to revise their recommendation upward or at least maintain it, not revise downward due to keeping a good relationship with management for private information and/or their conflict of interest. By counting the number of pages in analyst research reports, I provide the first empirical evidence of a stark contrast between a longer analyst report and a longer annual report.

Based on textual analysis of 81,826 10-Ks filed to the Securities and Exchange Commission (SEC) by U.S. firms during 1998-2013, the second essay documents the positive relationship of environmental disclosure with litigation risk which is another bad news. The essay also finds that environmental disclosure is mean reverting since bad news is more likely to be concealed relative to good news. Additionally, the essay shows that negative environmental information is disclosed more than positive environmental information in 10-Ks. Overall, the results identify disclosed environmental information as bad news that managers tend to hoard inside their firm. If environmental disclosure is negative news, then it is expected that the stock market negatively reacts to it around a 10-K filing date. The essay confirms this by documenting a significantly negative association of environmental disclosure with cumulative abnormal returns two days before and after the filing date. To the extent that disclosed environmental information in 10-Ks is bad news, I am able to investigate the effect of environmental disclosure on the future crash risk based on managers' bad-news-hoarding hypothesis. I provide empirical evidence that a firm with more environmental disclosure is less likely to experience major stock price drops in the future because of less of the managers' bad news hoarding tendency. The logit regression shows that a one standard deviation increase of environmental disclosure reduces the odds of a future crash risk by 10%, holding everything else constant. Further, using two exogenous shocks as an instrumental variable, I identify a potential causality, over and above mitigating potential endogeneity issues. Overall, the results are consistent with the idea that firms benefit from non-financial information disclosure.

Using a pattern search algorithm (i.e., regular expression) on the headlines of 81,762 forecasts during 2000-2014, the third essay examines the relative value of private and public information sources in analysts' earnings forecasts for U.S. firms. As an information intermediary, analysts access a *private* and/or *public* information source of a firm to make forecasts for investors. Previous studies consistently find a higher accuracy of forecasts made based on private information sources. Two sources, however, might equally be useful for analysts to reduce forecast error. The essay finds no significant difference between a single private and a single public information source in terms of analysts' earnings forecast accuracy, but an additional private information source might *cause* an increase in forecast accuracy. Given that an additional private source requires more efforts by analysts even without information advantage, investors highly appreciate the efforts by more strongly reacting to forecasts containing the private information. This new perspective makes the essay to be differentiated from previous literature supporting analysts' information advantage hypothesis. Further analysis shows that the combination of one management and one non-management private information source tends to produce the highest forecast accuracy and the strongest market reaction.

Overall, three essays document that the stock market favorably reacts to the forecast credibility-enhancing effort and the private information source-accessing effort by analysts. The essay also shows that environmental disclosure in firms' annual reports plays a role in reducing the probability of future stock price crash risk.